Systematic review of computational methods for oil & gas exploration and production risk indicators

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Abstract. The increasing concerns of stakeholders about environment and safety demand Petroleum industry to continuously reduce operational risks. Regulators and Industry Associations have been using several risk indicators for decades aiming to compare risk levels for facilities. These indicators play an important role to optimize resources defining priorities for audits and for other efforts to improve safety levels. However, numerous risk indicators are Lagging (Reactive) Indicators, which means that they only measure past events such as occurrence of incidents. Since these indicators are related to significant but rare accidents, they provide limited capacity for taking preventive actions. Furthermore, several indicators rely on subjective considerations of technicians to adjust importance of variables to determine risk level. The result may vary depending on specialist teams which suggest that the adjustments might not be the optimal solution to point out risk level. Petroleum industry is going through digital revolution and many novel emerging solutions based on computational methods are changing Oil & Gas exploration and production operations. Hence, the aim of this paper is to provide a systematic review of Optimization and Machine Learning methods to set risk indicators in Oil & Gas facilities. The review identifies 237 publications in past 10 years related to risk indicators in three major web-based academic libraries. We selected 27 papers using defined selection and quality criteria. Then, we grouped the studies according to definition methods of indicators in a map of findings, highlighting benefits, limitations, and strengths. As result, we attempted to envision the future of Oil & Gas risk indicators by emphasizing gaps, and possible setbacks or improvement opportunities of studied methods, paving the way for upcoming research on this topic.

Keywords: Systematic Review, Risk Indicators, Optimization, Machine Learning, Oil & Gas

1 Introduction

High complexity and risk industries are subject to major accidents that can influence public opinion reducing the level of acceptance of such activities. Although the industry of Oil & Gas exploration and production increases continuously efforts to elevate operational safety levels, high impact accidents still occurs and these efforts have technical and financial limitation. Moreover, regulators (public authorities), industry associations, and operators are continuously searching for more efficient ways to elevate industry safety levels. However, it is still a challenging task to find an issue sign that can lead to a potential accident with great impacts (Swuste et al. [1]).

Therefore, to identify good risk indicators in order to prioritize actions and avoid main accidents is one of the most important unsolved issues in safety research (Tang et al. [2]). Although there is no consensus in such division, indicators are traditionally classified in two categories: Leading (or proactive) indicators and Legging (or reactive) indicators. Leading indicators are measurements or observations of states that indicate deviation to ideal process (as delayed inspection number), meanwhile Lagging indicators reflect a consequence of process problems (as incidents). However, it is difficult to establish a straight correlation between indicators and major accidents (Thorsen and Njã [3]).

Skogdalen and Vinnem [4] and others also relate indicators to technical (as the number of overdue inspections, production capacity) or Human and Organization Factors (HOF), e.g. communication, safety climate, training, procedure compliance level. Researchers, regulators, and industry associations have been considering several indicators. Therefore, Health and Safety Executive [5] describes prerequisites for good measure of safety under the `SMART` concept: `S`pecific - it should represent a domain; `M`easurable - it shall be quantitative data; `A`ttainable/`A`chievable - it can be obtainable in a feasible way; `R`ealistic/`R`elevant - it must be linked to an aspect of interest; `T`imebound/`T`ime-specific - it can be traceable over time.

Moreover, to allocate resources to improve offshore safety, Almeida et al. [6] propose Global Indicators to rank units by safety condition. Global indicators combine a set of indicators using a specific methodology estimating a comparable risk level. Hence, management can prioritize actions such as audits or investments in the most critical units.

The indicators choice plays an important role in safety risk evaluation (Johansen and Rausand [7]). The present work aims to find computational methods to determine Oil & Gas risk indicators highlighting the strengths and limitations of each solution. This work follows a systematic review methodology to gather the past 10 years of literature about computational solutions related to risk indicators for Oil & Gas production facilities.

2 Methods

The systematic review is an important tool to gather literature information about defined research question. In this work, we use an online tool designed to perform systematic literature reviews based on Kitchenham [8] guideline for review within the context of Software Engineering called Parsifal. Full project can be found at https://parsif.al/rafaelalbuq/review-of-computational-methods-for-oil-gas-exploration-and-production-safety-index/. This guideline contains several aspect of the most common pattern for systematic reviews PRISMA (Statement for Reporting Systematic Reviews and Meta-Analyses) Liberati et al. [9].

The first step to develop this study following this methodology is to elaborate research questions. Aslam and Emmanuel [10] suggest PICO (population, intervention, control, and outcomes) criteria to elaborate research questions. Therefore, in this present work, the PICO parameter population is identified as "risk indicators" in "Oil & Gas industry" context. The intervention considers both computational and traditional methods (Risk Management) comparing between methods. The expected outcome is a set of risk indicators definition methods answering these questions: What is the best method to identify risk indicators to guide Regulators' audits? What are the strengths and limitations of each solution? What is the computation method tested to define Oil & Gas risk indicators?

2.1 Online database search

In our work, we include the following online abstract and citation databases: ACM Digital Library, IEEE Digital Library and Scopus. The choice of these three libraries was almost arbitrary and was based on common online databases used by authors and the fact that this are partially integrate to the online systematic review Parsifal. It is possible to define base search string from research question and PICO parameters. This approach lead to a base search string: (RISK INDICATORS) AND (RISK MANAGEMENT OR MACHINE LEARNING OR OPTIMIZATION) AND (OIL) AND (GAS) AND PUBYEAR $>$ 2010. This string had to be adapted to each database keeping the premise of searching metadata include at least title, keyword and abstract. As result, the search returned the following studies at each database: ACM Digital Library: 1, IEEE Digital Library: 12 and Scopus: 224.

2.2 Criteria for inclusion and exclusion

We defined inclusion/exclusion criteria aiming to filter the number of results. To consider computational methods in risk indicators and Oil & Gas risk indicators methods, the inclusion criteria consist of: machine learning for risk indicators; optimization for risk indicators; risk indicators articles for Oil & Gas.

Once the abstract or keywords refer to one of these topics, we included the study. The search results that were excluded fall in one of these exclusion criteria:

DUPLICATE - works that were duplicate from multiple databases. One of them is excluded.

FULL TEXT NOT ACCESSIBLE BY CAPES - the Brazilian federal government agency CAPES provides access to more than 50.000 journals to universities. Unfortunately, not all works found in the search were available. So, some papers were removed due to lack of access.

BOOKS - books references were also excluded.

DOES NOT IDENTIFY RISK FOR A SINGLE INSTALLATION - as long the systematic review focus on offshore units, studies that do not may be applied to a single installation.

FINANCIAL RISK INDICATOR - safety is the objective of this study. Hence, we discarded studies that focus on the financial aspect and do not involve safety issues.

HEALTH RELATED STUDY - studies related to medical or health were also excluded.

NON-INDUSTRIAL EVALUATION - studies that focus deviate from industrial facilities.

OLDER THAN 2010 - we restricted the search for works published no longer than ten (10) years.

STUDIES WITHOUT A CLEAR RISK INDICATORS DEFINITION - also were excluded studies not related to risk indicators.

STUDY FOR EQUIPMENT - some works focus only on equipment or systems and do not relate to overall installation risk. We removed these works as well.

2.3 Screening

The second filter in works to be evaluated in a Systematic Review is the Quality Assessment. In this step, each paper receives a grade based on defined criteria. Six question defines these criteria. The answer to these questions generates grades between 0 (NO), 0.5 (PARTIALLY) and 1 (YES). Full text is evaluate at this steps. The formulated questions were:

1. Includes machine learning, statistic model, or optimization technique?
2. Representative number of Oil & Gas units evaluated? (YES $\approx$ 10 or more, PARTIALLY= more than one)
3. Does the study have a systematic evaluation? (well designed experiment or comparison criteria)
4. Does the authors describe benefits? (strengths)
5. Does the authors describe limitations? (weakness)
6. Is there a case study?

We set the grade cut at 3.0 and include all studies above this grade. The aforementioned question tried to narrow down study content to better answer the research questions. Question 1 considered the methods involved in each study. The number of offshore units is considered in Question 2. Studies considering around or over 10 facilities received the maximum grade for the question. If it is more than one unit, the grade is 0.5. Question 3 tries to evaluate study consistency and systematic. Question 4 and 5 respectively analyze description benefits and limitations. The application in a study case adds one point to the grade due to Question 6.

2.4 Parameters extracted

The content of the remaining works was organized and we extracted relevant information about each one. We extract pieces of information like authors, publish date, the number of units evaluated in the study, the method applied (REVIEW, MACHINE LEARNING, STATISTICAL and OPTIMIZATION), study aim, case study, a summary of results, and conclusion. Figure 1 summarizes all search, exclusion and screening process showing how many works were excluded and remained in each step. Also, it shows the final quantity of works divided by the methods used.

3 Results

Most of the selected works focus on risk analysis, but have some degree of relation with indicators. Only ten of them are specific on indicators (Plácido et al. [11], Almeida et al. [6], Khvostina et al. [12], Bergh et al. [13], Ancione et al. [14], Kongsvik et al. [15], Swuste et al. [1], Sultana et al. [16], Thorsen and Njã [3] and Tang et al. [2]). We elaborated a comparative table including all selected articles, but it was not possible to include it due to congress article size limitation (the table takes five pages). Therefore, this section is organized in groups of articles highlighting the common characteristics and the main differences. With the purpose to collect their characteristics, we split the selected studies into five classes according to their methodology: Statistical, Deterministic, Optimization, Machine Learning, and Review. In the next sections, we detail some features of the works selected.

3.1 Statistics based

Twelve selected works use a statistical technique for either select indicators, define their weights, or evaluate representatives. Antonovsky et al. [17] identified and ranked frequent human factors that affect maintenance-related failures to prevent an accident. This work applied a statistical test to evaluate Performance-Shaping Factors (PSFs) concerning severity. Khvostina et al. [12] presented an algorithm for probabilistic environmental risk

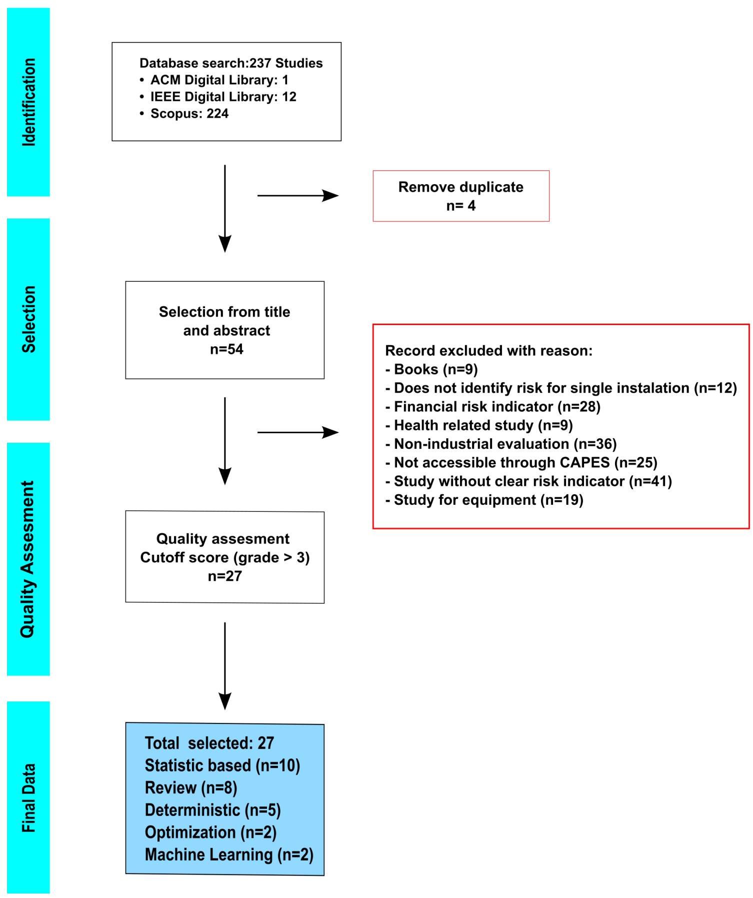

Figure 1. Diagram describing search strategy and the search results.

assessment of enterprises based on risk indicators. The study provided a method to grade the level of environmental risk based on fuzzy evaluation of experts' assessment.

Bergh et al. [13] investigated the Psycho-social Risk Indicator (PRI) relationship with Hydrocarbon Leaks (HL) on Norwegian Oil & Gas producing platforms. The study concludes that there is a correlation between PRI and HL which indicates that PRI must be considered as a proactive measure. Strand and Lundteigen [18] proposed Human Reliability Analysis (HRA) for Risk OMT (Organisational, Human and Technical) extension to improve human error analysis in well-drilling activities. The proposed method of risk analysis enables the calculation of human error probability without Bayesian Belief Network software. Kongsvik et al. [15] empirically explored relations between a proposed safety climate indicators and hydrocarbon leaks. The work affirms that there is significant statistical correlation between safety climate indicators and leaks. Ancione et al. [14] proposed a dynamic risk analysis for Floating Production Storage and Offloading (FPSO) crane operation through the aggregation of a set of risk indicators as a study case. The aim is to integrate dynamic features to risk assessment procedures in order to enable early actions that can reduce the probability of undesired events. The authors applied a sensitivity model (Birnbaum's measure, see [14]) to evaluate barrier importance.

Gendler and Prokhorova [19] performed a correlation analysis of Russia mining industry injury risk and geographic regions, evaluating risk values based on statistical data for each region of the Arctic zone and estimating a relative change in injury risks over the past 10 years. Olsen et al. [20] used descriptive statistics to investigate the relationships between work climate and HL through questionnaires. Results prove consistency on questionnaire answers and also found a significant correlation between climate factors and HL in the post-survey period. Tang et al. [2] ranked safety indicators to offshore Oil & Gas processing in Malaysia based on safety personal experience. They statistically compare indicators to the probability of incident occurrence but it could not confirm correlations between both ratings. However, it found correlations among the safety factors enabling them to cluster them into groups. Lee et al. [21] showed how Dynamic Risk Analysis (DRA) can be validated based on risk analysis validation technique through a case study in the Oil & Gas industry. To validate results, this works considered three parallel strategies: (i) reality check, (ii) benchmark, and (iii) peer review. The benchmark used static metrics to compare DRA methods.

3.2 Deterministic

Traditional approaches to choose and/or gather risk indicators rely on industry specialist opinions. Authors usually apply weighted sum to aggregate or prioritize indicators. As long as a direct relationship between the indicator and major accidents is difficult to find, specialist opinion is the empiric tool to determine the weights.

Almeida et al. [6] proposed global indicators from weighted process safety indicators to identify weaknesses at individual platforms. Bucelli et al. [22] suggested a slight dynamic approach through a risk barometer technique that can aggregate data concerning the barrier element status aiming to deal with risk over time. Sultana et al. [16] described a workflow to identify risks indicators based on the STAMP (System-Theoretic Accident Model and Processes) accident causation model that considers both human and organizational factors and technical elements. Thorsen and Njã [3] evaluated major risk indicators and proposed a set of indicators following comprehensiveness, applicability, and manageability criteria. Skogdalen and Vinnem [4] evaluated the influence of legislation on Quantitative Risk Analyses (QRA) development in the Norwegian offshore industry, verifying how Human and Organizational Factors (HOF) are considered in QRA and classifying it in integration levels.

All of these works present relatively simple to use techniques as an advantage. However, they require empirical information that impacts reproducibility.

3.3 Optimization

Only two papers described optimization methods. Chen et al. [23] proposed an extended multi-objective optimization by ratio analysis and full multiplicative form (MULTIMOORA) based on ordered weighted geometric average (OWGA) operator and Choquet integral for risk assessment through two case studies demonstrating its application. Hence, the model focus on potential failure modes evaluating the importance of each indicator. In another work, Khalilzadeh et al. [24] analyzed failure mode (FMEA) with fuzzy multi-criteria decision-making (MCDM) methods and multi-objective programming model in Oil & Gas construction projects. The model manages to rank the risk of Oil & Gas construction projects in Iran.

3.4 Machine Learning

This review selected two works involving machine learning methods. Goel et al. [25] did an overview of novel information technologies including machine for plant operations, maintenance, environmental protection, and process safety. They demonstrate the potential of these technologies in the industry through study cases like equipment failure prediction and text mining to organize accident data. Yang et al. [26] used backpropagation network (BPN) theory to establish the risk index of offshore projects. They concluded that, although BPN shares some limitations with other models, it can be used to project risk evaluation with advantages because it is well suited for complex non-linear models.

3.5 Review

We found seven studies focused on reviewing available information. Many of them target risk assessment and we select works that, at least, involve indicators. Plácido et al. [11] searched in the literature and did a comparative analysis of the QRA process in the Oil & Gas megaproject involving managers and consultant opinion. The work concludes that there are gaps and opportunities for improvement of the risk analysis process. In another work, Zhen et al. [27] investigated Risk Influence Factors (RIF) in QRA models. This study observed that there are few methods available using indicators for measuring the status of non-technical RIFs. Swuste et al. [1] evaluated if and which indicators can provide insight and knowledge of process safety level concluding that indicators are able to show relevant changes in risk levels but still can not predict major accidents. Yang et al. [28] reviewed eleven risk influence frameworks that consider human and organizational factors. The works describe that most risk influence frameworks focus on update QRA from the design phase that could generate gaps to activity-related risk. It also proposes a combination of both RIF and frameworks as a good alternative to model and estimate activity performance risk. Villa et al. [29] reviewed Risk Assessment (RA) methodologies and relevant applications for the chemical process proposing a novel classification approach to compare RA evolution and advantages/limitations of the dynamic approach.

Folch-Calvo et al. [30] also analyzed relevant risk methodologies. This work presents a discussion about the advantages and drawbacks of methodologies include standards/directives/regulation, preventive, probabilistic, traditional modern, and dynamic risk methodologies and their applicability over time. They also proposed a work procedure (to collect and evaluate what can cause an accident) that creates real-time analysis and immediate response through the integration of sequential methodologies (traditional), safety barriers, dynamic risk assessment, and Industry 4.0 methods supplemented by data mining processes. Basheer et al. [31] described an overview of major risk assessment in the Chemical industry through a comparison of main methods of risk assessment. Tukiman et al. [32] provided a systematic review of offshore Risk Management (RM) to guide further studies. It suggests that Oil & Gas companies should adopt the RM approach that fits the installation or operation characteristics. They realized that literature is concentrated in risk identification and risk assessment lacking risk response and combination identification/response.

4 Conclusions

This work presents a systematic review aiming to summarize studies that use modern techniques for identifying risk indicators to prevent major accidents. Traditional techniques to elect or gather indicators into global ones rely on weighted aggregation frequently based on empirical safety specialists' opinions. Occasionally some authors apply statistic techniques such Bayesian Network to rank indicators by importance (Ahmadi et al. [33], Zhen et al. [27], Skogdalen and Vinnem [4], Yang et al. [28]). These techniques are far from provide optimal results once, often, no straight relation to accident can be detected.

Recently, ones investigate risk evaluation and equipment failure through optimizations or machine learning methods with promising results (Yang et al. [26], Khalilzadeh et al. [24]). However, few works address the risk indicators problem. The use of these techniques may represent the future of Oil and Gas risk indicators. If the search criteria/string were broadening (excluding word "indicators") much more results including computational techniques would be found.

Literature review showed that finding a correlation between risk indicators and major accident hazards is not an easy task due to the high complexity of accident scenarios. This fact can be considered as the main setback for future improvements in risk indicators. However, some of evaluated studies suggests some relation on safety culture and human factors indicators and accident proportion. Another opportunity of future work is a deeper analysis focused on available indicators, maybe including a meta-analysis.

Future works can investigate possible optimization methods, statistical analysis, and machine learning techniques to identify risk indicators. The long-term objective is to propose a methodology to either define audit target units or provide another resource to improving safety levels in an efficient way.

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