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Technical Paper

Artificial intelligence and decision-making in situations of uncertainty

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Abstract

O&G companies are being compelled to maximize their assets' value and optimize investments, in order to enhance process efficiency and wisely decide when and where invest to reach their business goals. In consequence of such a scenario, companies need to apply new technical resources to accelerate the development of O&G exploration processes and adapt to making decisions in situations characterized by uncertainty. In this sense, Artificial Intelligence (AI) and Data Science in general have demonstrated to be a mighty technology in supporting complex and complicated tasks. This paper describes some AI-based applications tailored to specific needs of O&G industry processes, highlighting some research and development efforts that the authors' institution has made in the field of predictive intelligence and which might meet those needs. For instance, machine learning and deep learning applications to identify engineering assets in degraded conditions, from images captured by drones; machine learning or PCA (Principal Components Analysis) techniques to make predictive models more easily treatable in order to identify failure patterns of key equipment subjected to stress and unforeseen conditions of use; and approaches to cope with uncertainties in asset operation and maintenance, including data elicitation with experts and probabilistics models. The computational intelligence thus employed for predictive purposes can bring insights in situations of uncertainty – or when data is unavailable – and consequently support organizational decisions, since the recent complex processes impose hard challenges and huge costs to O&G companies in exploring efficiently the resources and maintain the production goals.

Keywords: Artificial intelligence. Decision-making. Machine learning. O&G industry. Predictive maintenance

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1. Introduction

With declining costs in worldwide oil production and the increasing of shorter life-cycle projects, oil companies are becoming more selective since they are pressured to compete by funds and start producing quickly. To some extent, global oil prices drop is remodeling Oil & Gas (O&G) industry, requiring greater dynamism in investment decision-making cycle. Similarly, operational issues demand speeder and more assertive decisions in order to reduce costs and keep the production interruption time down.

Confronting such trends, companies are compelled to maximize their assets' value and optimize investments, in order to enhance process efficiency and wisely decide when and where invest to reach their business goals. Besides, the global productive forces are facing the immediate need of migrating to a sustainable and carbon-free economy, reducing environmental impacts and fostering social responsibility.

Accordingly, O&G companies are deploying renewable projects, based on clearer energy, and seeking to achieve best energy-efficient indexes. Other energy matrices, such as the wind and solar, are expanding massively, as well as rules for the global production of electric cars and the growth of alternative transportation (carpooling and biking) in the world landscape have changed the societal perception in terms of energy consumption and carbon footprint. One can perceive that these new business models and supply-demand arrangements impact companies and society, requiring therefore cutting-edge solutions to deal with the changing scenario.

Brazil adds other peculiarities to this panorama of changes and challenges. Despite its expressive numbers about O&G production, this performance is just a fraction of the amount it could be, the whole potential is unknown (ANP, 2018). The national offshore and onshore oil production have declining in last years, and the well drilling dropped circa of 70 and 80%, respectively (ANP, 2018). In accordance with the Agency, innovation and technology should be applied to explore the national potential.

In consequence of such a complex scenario, Brazil needs to apply new technical resources to accelerate the development of O&G exploration processes and adapt to making decisions in situations characterized by uncertainty. In this sense, Artificial Intelligence (AI) and Data Science in general have demonstrated to be a mighty technology in supporting complex and complicated tasks.

This paper describes some AI-based applications tailored to specific needs of O&G industry processes, highlighting some research and development efforts that the authors' institution has made in the field of predictive intelligence. For instance, machine learning and deep learning applications to identify engineering assets in degraded conditions, from images captured by drones; machine learning or PCA (Principal Components Analysis) techniques to make predictive models more easily treatable in order to identify failure patterns of key equipment subjected to stress and unforeseen conditions of use; and approaches to cope with uncertainties in asset operation and maintenance, including data elicitation with experts and probabilistics models.

2. AI in O&G scenario

Several AI applications have recently been adopted in the O&G industry and have gained huge acceptance (Hanga & Kovalchuk, 2019), and more should be discovered due to an increasingly widespread use. The academic production around AI driven to O&G industry challenges has grown asymptotically, mainly if we bring the focus to machine learning and its advances as deep learning. In the last ten years this growth has been greater than 1,100% (in accordance to a literature review being carried out by the authors), a boom also observed in other fields of application. Regarding the movement in the worldwide economy, a Markets and Markets report (2017) forecasts a growth trend of the AI value in the O&G industry, reaching US$2.85 billion in 2022.

To play their roles satisfactorily, decision-makers, planners, economists, developers and engineers in O&G activities are constantly being challenged by scenarios that change at an astonishing speed due to a set of unpredictable factors. The driving forces that condition complex changes in various sectors of industry and society take particular forms when it comes to energy sources and oil fields.

2.1. Complexity and uncertatinties

Uncertainties in O&G industry have been addressed under various factors, either in function of geological issues or investments decisions (Ahmadi, Manera, & Sadeghzadeh, 2019). From the perspective of predicting oil price and making decisions more assertive, there are many factors that interact with each other and obscure the scenario by hiding nonlinear consequences and weakening models that disregard the complex dynamics behind the forces that orchestrate the supply and demand relationships. Among such factors are currency fluctuation, geopolitical conflicts, and natural disasters (Wang et al, 2018). More recently, an unpredictable factor may be added to the nature domain: the Covid-19 pandemic, with radical changes in social behavior and energy consumption, to name just a few of its consequences in the economic and social sphere. From the perspective of geological issues, the identification of fractures or residual oil as well as seismic exploration are no less complex neither free from uncertainties, requiring more sophisticated models and higher quality data for predicting and planning purposes.

In the last decade, Bickel and Bratvold had already pointed out that O&G professionals realize that goods decisions depend on more information (2008) and the type and quality of information impact decisions (Bratvold, Bickel, & Lohne, 2009). An approach to risk assessment of critical operations is presented by Veland and Aven with the purpose of better dealing with uncertainties and addressing unforeseen events (2015). Ani, Oluyemi, Petrovski and Rezaei-Gomari (2016), in turn, carry out an analysis of several techniques to characterize reservoir parameters and face uncertainties arising from geological complexities, including the recent modeling developments to adopt artificial intelligence algorithms.

Yet related to reservoir issues, Ertekin and Sun (2019) present a review of artificial intelligence algorithms to solve problems that affect this area. In another review of AI methods for supporting decisions in O&G areas as oil production and CO_2 sequestration, Rahmanifard and Plaksina (2019) underline the importance of these methods, including their combination, in terms of optimizing decision-making and solutions.

2.2. Counterbalancing uncertainties with intelligence

Situations of uncertainty arrive in the design, operation, and maintenance of complex systems. Besides its ineherent complexity, there is the usual situation of short project award and short execution time of Oil and Gas Systems (OGS) that have many challenges for which AI can provide useful approaches and solutions. As one can see in the technical-scientific production and in the profusion of literature surveys being carried out recently, AI-based tools can positively impact companies, supporting many activities of the O&G industry, from design to production pipeline.

As in other areas, it can remove data redundancy, correct inconsistent data, overcome data gaps and augment data. This latter is especially useful when data are scarce, both for the absence of historical series and for being extremely expensive to obtain them. It may embed virtual assistants or robots either for boosting productivity or reducing risks to humans.

AI embraces a number of techniques, for example, machine learning, artificial neural networks, decision tree, predictive analytics, generative adversarial network and so, which can be properly useful in transforming data into information able to provide managerial insights throughout many exploration and production processes of the O&G industry. The new intelligent wave of technology may be applied from prospection and drilling up to energy production and the control of dangerous tasks. Data interpretation provide by AI can contrast and detect geological features, besides recognize patterns and identify several kinds of objects and engineering assets, as well as predicting recoverable hydrocarbons.

Indeed, in the last years a significative number of AI-based research and development have been reported, with varied applications in the O&G sector and using many techniques to reduce uncertainties, forecast price fluctuations and predict critical events – see for example (Nasser, Montasir, Zawawi, & Alsubal, 2020), (Li, Yu, Cao, Tian, & Cheng, 2020), (Khamis, Elhaj, & Abdulraheem, 2020), (Hanga & Kovalchuk, 2019) and (Wang et al., 2018).

Furthermore, uncertainties to be diminished or ever overcome is not just a desire for decision-makers involved geological issues and oil price forecasting, as we had initially argued. Managers and operational engineers in charge of maintenance actions facing real challenges when it comes to repairing critical equipment, both in terms of productivity and, what is more urgent, in terms of physical and environmental safety. Predictive intelligence, a particularly challenging field of application for data science (cf. Holanda, Adorni, & Souza, 2019; Kathidjiotis, Kolomvatsos, & Anagnostopoulos, 2020), is a mean for cost savings and for adoptig more safety procedures in the production pipeline. It is a discipline that has been expanding, increasing the range of alternatives to tackle uncertainties and support decision-making either in operational and security issues or in a strategic level of investments and process optimization.

Among different sectors of the petrochemical industry, crude oil refineries are also surrounded by uncertainties in addition to be considered high-risk workplaces. Such risks are associated with critical parameters – for example, pressure and temperature – and malfunctioning of equipment in its production lines can cause unexpected damages and accidents. For example, an area with potential risks is related to furnaces pipelines, which is directly related to temperature variation (Valus, Fontoura, Serfaty, & Nunhez, 2017). Zaranezhad, Mahabadi and Dehghani (2019) present forecasting models for accidents related to maintenance and prediction in oil refineries, by using artificial neural networks, fuzzy systems, and metaheuristic algorithms.

In general, scalable predictive maintenance has met operational managers who need to prioritize actions and better organize the interventions of field teams. It allows monitoring conditions and foreseeing equipment degeneration, points of failure and critical occurrences, also acting to optimize preventive maintenance and, above all, to minimize the need for corrective actions. The technological march of the Data Science, with unprecedented processing power and the possibility of complex computing of techniques such as advanced analytics and big data (cf. Cadei et al., 2019), machine learning, computer vision, recursive neural networks and fault prognosis (cf. Ran, Zhou, Lin, Wen, & Deng, 2019; Rensburg, 2018) has allowed to act in this direction.

3. Some predictive approaches to support decisions

Analytics-based modeling and AI techniques for predicting critical events and supporting decisions to optimize maintenance are the points on which we have made R&D efforts and which we present some approaches as follows. Even though these projects have been developed for predictive maintenance applications in other energy sectors, such as the electrical utilities, the analytical approach can also be used to meet specific demands in the O&G industry.

3.1. Analyzing images

One approach concerns the use of computer vision for inspection of assets in power lines, from images captured by drones. The AI technique is primarily based on machine learning and uses Convolutional Neural Networks (CNNs) for the analysis and interpretation of images captured in regular inspections. The main objective is identify and classify a critical asset in accordance with their degradation level, in case of elements exposed to climatic factors and aging due to continued use, and thus support predictive maintenance decisions (Santos et al., submitted for publication).

3.2. Reducing analysis components

Another approach deals with analyzes for detecting incipient failures in critical power distribution equipment, using indicators derived from actual oscillography data and PCA (Principal Components Analysis) technique to reduce the number of variables to be analyzed. PCA allows the suppression of highly correlated components that can make analysis difficult. The predictive action made possible by this technique is based on the assessment of physical parameters of the equipment (e.g., temperature, vibration), measured in real time by sensors (for example, oscillographs) for detecting possible situations of quality degradation in the power line that require maintenance intervention. (Adorni, Souza, Nader, & Holanda, 2019).

3.3. Dealing with uncertainties in the asset operation and maintenance

Asset operation and maintenance is another field of activites that demands predictive solutions. To forecast anomalies in complex assets like pumps, for example, two modelling approaches are used: state change and expert based modeling. For the first one the main drawbacks pointed in (Carpenter, 2020) are high cost and highly skilled efforts. For the later, although costing less, it is difficult to detect experts disjointed opinions, the final score consensus generally converging to known anomalies. On the other hand, when a large amount of equipment asset failure data is available Machine Learning techniques can be used like decision tree, neural network etc.

All the three techniques are currently used in many engineering fields. To get a first insight of the asset behavior the expert-based modelling is very appropriated as it is easy to apply, have low cost and the results are well understood by the experts. Aiming at collecting and synthesizing the expert opinions, several techniques are available, for example, brainstorming, document analysis, focus group, interviews etc. The elicitation process uses such techniques to provide or elicit a response to well defined problems.

In the following, two techniques we are investigating and structuring are presented to: (i) overcome with the main expert-based modelling drawbacks namely, (ii) detect conflicting opinions and (iii) point out anomalous behavior not directly addressed during the elicitation process.

3.3.1. Detecting conflicting opinions

Oil and Gas sectors like refinery have a complex plant that requires high availability of its components to maintain the production. Compressors, pumps, manifolds etc., all of them contribute for the plant availability. The maintenance management requires quantitative evaluation of the reliability of each component to assure the plant overall availability.

Failure data are collected but experts that should be involved in the reliability assessment of their systems, as they can contribute with their experience. The procedures for eliciting expert knowledge are generally qualitative and in many cases scorecard method is used. Scorecard method is a composite index that relies on the weights given by the experts, representing their opinion about the asset reliability attributes being analyzed and the corresponding risk. The elicitation result is used to derive the asset reliability indicators and, thus, conflicting opinions should be detected to brought news discussions up and getting better insights of the phenomena.

PCA (Dunteman, 1989) is multivariate technique that can provide objective weights through the evaluation of the eigenvalues of the many attributes. The weight of the importance of each attribute is quantified by the eigenvalues. This technique is suggested in (Galar, Berges, Sandborn, & Kumar, 2014) as a possible aggregation method. It will be used to correlate subjective attribute weights and final risk evaluation with PCA eigenvalues to detect conflicting opinions that should reanalyzed.

In the next subsections a hypothetical example of elicitation is used (real scores set but taken from a different context) where 10 experts of a site production weigh an asset failure probability attributes (1 to 5 scale). Similarly as carried out in (Holanda, Souza, Adorni, & Nader, submitted for publication), four attributes are considered:

- Time to failure: 1 to 5, as time to failure decreases;
- Degradation condition: 1 to 5, as the item presents a higher degradation;
- Replacement need: 1 to 5, as the replacement is more urgent;
- Risk: 1 to 5, as the risk increases.

For the elicitation process, the numerical classification of the attributes obeys the following correspondence: 1 (very low), 2 (low), 3 (medium), 4 (high), 5 (very high).

Table 1 - Asset reliability elicitation result

Expert	Time to failure	Degradation condition	Replacement need	Risk
1	4	1	2	2
2	1	1	3	2
3	4	5	5	5
4	2	1	2	2
5	1	1	1	2
6	1	2	1	1
7	3	1	3	3
8	1	1	1	1
9	2	1	1	1
10	1	1	1	1

Source: elaborated by the authors

The question in this example of Table 1 is the analysis to detect conflicting opinions between the “Risk” and the other attributes. PCA is applied to the first three attributes and the eigenvalues ratios are: 75,3%, 17,1% and 7,6% respectively. Such a condition suggests that the “Risk” attribute is considered by the experts to be highly impacted by the attribute “Time to failure”.

In turn, the quantitative “Risk” is derived with basis on the PCA eigenvalues ratios. When the “Risk” weight is not between ± 20% of the PCA score, the item should be investigated. By applying this approach, the first is a conflicting opinion needing reinvestigation as far as the “Risk” seems undervalued given the “Time to failure” weight.

3.3.2. Deriving the failure distribution time

Here again we follow the methodolology described in (Holanda et al., submitted for publication), and the failure time distribution is used to estimate the reliability of an asset and the need, or better, the time for its replacement, assuming a given reliability risk. The applied method provides means to quantitatively derive the reliability based on the qualitative attribute scores. In this case, it is based on two attributes shown in previous subsection, i.e., “Time to failure” and “Degradation condition”.

To derive the distribution function, two parameters are needed: the TTF (Time To Failure) and the standard deviation (σ). In this approcach, the TTF is estimated by the elicitation process, whereas σ is quantified based on the qualitative scores. When it comes to mechanical equipment, σ is lower than the mean, diminishing with the degradation time. Table 2 ilustrates results obtained with this approach, relating qualitative score values and the proposed σ as a percentage of the TTF.

Table 2 – TTF and qualitative scores

Score	TTF (years)	Degradation condition	Replacement need (years)	σ
1	-	Normal	Major repair	20%
2	10	Altered	Planning > 10	20%
3	5	No data	Planning 5 to 10	20%
4	1	Deteriorated	Planning 2 to 5	15%
5	0.5	Imminent	Planning < 2	10%

Source: elaborated by the authors

Considering the distribution function is not known, at least a priori, a weighted model combining constant and non-constant failure rates is thus proposed. In this manner, one can derive the distribution function F_{am} (t) by weighting two functions: the Exponential, Exp(μ), and the Normal, $N(\mu,\sigma)$. Such a formulation is expressed in (1).

$$F_{am}(t) = p * \int_0^t N(\mu,\sigma) + (1-p) * \int_0^t Exp(\mu) \qquad (1)$$

In this case, the weight parameter is the confidence level of the Normal function, taking into account the mean and 3σ, in such a way that $p = 99.5$. Putting in another way, 99.5% of the failures will occur in the interval defined by the mean ± 3σ. The reliability is the complement of F_{am}, i.e., $R_{am}(t) = 1 - F_{am}(t)$ and expresses the asset survivability as a function of the time.

3.3.3. Analyzing planning risks

The first risk analysis considers the elicited time to replace in Table 2 of the subsection 3.3.2. Considering a reliability plan for which the asset survivability should be the range [10%, 90%], the time to replace based on $R_{am}(t)$ application is: *score 2,* > 8 years; *score 3*, 4 to 6 years; *score 4*, 1 to 1.5 years, and *score 5,* < 1 year. Considering the quantitative estimates of the Table 2, the elicited time to replace presents a high risk to failure, mainly for the scores 4 and 5, regarding the quantitative range of scores presented above. In this case the reliability curve falls abruptly around the elicited TTF.

3.4. Discussion

AI-based applications as we have shown in the first approach above, i.e., using computer vision from images captured by drones, may be applied as predictive intelligence in O&G operational process located onshore and offshore. Monitoring procedures based on image recognition allow to detect defective assets in hard-to-reach places and potential defects over several kilometers of pipelines, as well as to verify threats to the integrity of the tubes, by monitoring the conditions of the environment in which they are installed, such as soil erosion, landslides, pipe displacement. In this way, it is possible to act predictively.

PCA technique allows analyzing data from a plethora of assets monitored by sensors in any segment of the O&G value chain, for example, in fluid catalytic cracking units and in the distillation column, where one of the factors that can be monitored is the corrosivity and its interrelationship between the corrosive process and the process variables. In addition, PCA may be useful in recognizing and separating lithostratigraphic units, and in identifying aquifer formations and distinctions between hydraulic flow units (cf. Niculescu & Andrei, 2016).

The approach based on data elicitation may be applied to a plant in the O&G sector, so that each critical asset (equipment) can be subjected to an elicitation process with experts. The results thus obtained can contribute to the reliability and maintenance plan of that plant.

Anyway, there are always uncertainties associated with every estimate, due to the quality of the data, the heterogeneity of contexts, the approximation inherent to the modeling process, etc. Ppossible alternatives to increase the accuracy of the estimates are the combination of indicators (cf. Gallar et al., 2014) and the integration of analytical approaches (cf. Alves & Holanda, 2016), in order to compensate eventual biases and inaccuracies of each one in isolation.

4. Final remarks

This paper described some R&D efforts that the authors' institution has made in the field of AI-based applications for predictive intelligence and which might meet O&G industry needs. The computational intelligence thus employed for predictive purposes can bring insights in situations of uncertainty – or when data is unavailable – and consequently support organizational decisions, since the recent complex processes impose hard challenges and huge costs to O&G companies in exploring efficiently the resources and maintain the production goals.

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