Trustworthiness of subsea assets degradation model estimations and its influence on the reliability of risk-based decisions

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Abstract. Although subsea assets in the oil and gas (O&G) industry are very robust equipment, the consequences of their failures may be catastrophic for people, environment and companies. Nevertheless, the inspection procedures comprise measurement in loco with ROVs, which involve a high resource allocation in costs and planning. For this reason, O&G industries have been pushing a massive investment in digital technologies, like digital twins, with important simulation tools to estimate and predict the behavior of a process or the conditions of an asset. Digital twins for integrity management lay on several degradation models, the most relevant ones which subsea assets undergo, such as erosion and corrosion. In this context, the decision to inspect (or not) is driven by the outcomes from these degradation models, which are always a compromise between resource allocation and the risk associated with a catastrophic failure. It is called risk based inspection (RBI). This work aims to analyze how uncertainties related to the modeling process can influence the model outcomes and hence the reliability of the decisions based on them.

1. Introduction

The integrity management process of subsea assets has been relying on local measurements carried out by ROVs. Although it can provide very accurate results to the measurement point, it has some strong drawbacks. It is not easy to schedule an inspection, because of the restricted amount of companies able to accomplish this kind of specialized service. Moreover, it is a costly and time consuming process, both in planning and execution, which leads to the use of a lower measurement frequency than desired. Furthermore, due to asset design issues, the most critical point, the one that should be monitored, may not be reachable with ROVs.

In order to overcome these difficulties, digital models for the most relevant degradation phenomena for subsea assets have been developed. Through the monitoring of production parameters like pressure, temperature and flow, as well as fluid parameters such as viscosity and density, these models can be used to estimate and predict the degradation state of a subsea asset with a high sampling rate and low costs. One important example of these models is the DNV erosion model, outlined in DNV-RP-O501 [1] and presented in this paper.

Nonetheless, the reliability of their outcomes rely on several uncertainties associated with the used model and the input data. These uncertainties have different sources, coming from the input data and from the limitations regarding the modeling process, as detailed in section two.

These uncertainties are outlined in sections three and four, focusing on the DNV erosion model for subsea assets. Section five presents the main conclusions of this work.

2. Uncertainties associated with model estimations

Along the degradation analysis chain, from data gathering until model evaluations, uncertainty is present on data.

During the production stage, measurement systems outputs contribute with deviations like bias and statistical variations. Moreover, thermodynamic parameters like temperature and pressure, as well as wear, influence both measurand and sensor components. Then, data from measurement systems contain measurement uncertainty, generated by the environment, the measurement process, the measurement system and the measurand. Besides, income material and fabrication processes present variation and tolerances, which increase the uncertainty presented in data collected by sensors.

Since uncertainty may be regarded as the level of trustworthiness presented in data, it is clear that measurement uncertainties influence the quality of data gathered from sensors.

Data collected during project and production stages are stored in databases, to be accessed and processed by data-driven algorithms, like neural networks, random forest and support vector machines, which attempt to extract information and identify patterns from data. Furthermore, they intend to generate models from data, aiming to represent and predict the behavior of systems.

These algorithms use the huge computational power available today aiming the identification and extraction of information from acquired data, as well as crafting models from physical assets, which are able to describe its conditions, to diagnose possible faults, to predict its future behavior and to prescribe actions that should be taken, in order to reach a better future condition for the asset.

Another source of uncertainty is the capacity of data-driven models to represent physical phenomena, the inherent lack of knowledge associated with modeling a not completely known phenomenon.

If the amount of analyzed data is not enough to gather all relevant features, model outputs present an uncertainty related to the inability to represent the associated phenomenon. In other words, the model would be valid only while its data inputs are statistically similar to data used in its training. Extrapolations raise the level of uncertainty presented in model outcomes.

Moreover, some physical phenomena such as corrosion changes its behavior over time, which makes the prediction of its future states more difficult, lifting its uncertainty level too.

Then, uncertainties influence the quality of data gathered from sensors, which impact on the quality of data-driven models outcomes. Furthermore, simulation models have an intrinsic uncertainty, which also influences the estimates and predictions performed with them.

In order to assure the reliability of these results, it is crucial the understanding and evaluation of all relevant uncertainty sources.

To better understand the uncertainties associated with the usage of simulation models, some classifications have arisen during the last years [2]. The most known classes are epistemic and aleatoric uncertainties. Epistemic uncertainties can be related to the amount of ambiguity or imperfect knowledge embodied in the model, and aleatoric uncertainties describe the variability of the possible outcomes, being very associated with the variability of input data [3][4].

Both kinds are going to be better explored in the following sections, bringing the O&G industry case and conclusions.

3. Aleatoric uncertainties

Aleatoric uncertainties are related to the variability of model input parameters. Then, in order to understand their effects on the model outcomes, it is necessary to analyze each input of the model. Considering this paper, the DNV erosion model [1] is explored.

DNV-RP-O501 presents several erosion models, according to the relevant geometry of the subsea asset. Every model is based on equation (1) [1].

$$E_m = K \cdot U_p^n \cdot F(\alpha) \bullet m_p \tag{1}$$

- E_m: erosive wear rate [kg/s]
- K, n: empirical constants associated with the erosion relationship between particle material and eroded surface material, prescribed in DNV-RP-O501 for the most common values.
- U_p: average particle impact speed [m/s]
- α: average impact angle [rad]
- $F(\alpha)$: ductility factor of the surface material [ ]
- m_p: sand production rate [kg/s]

The usage of this model demands a pre-processing of data related to fluid properties, production and the design of the observed subsea asset. In this process, mathematical tools, like the "Blackoil model", may be useful in order to evaluate local parameters from topside measurements [1].

To evaluate the influence of the input variables on DNV erosion model estimation, each input parameter can be analyzed and described with a probabilistic distribution function. Then, a Monte Carlo simulation can be performed, aiming to learn the model output probabilistic distribution.

When using a mathematical model to describe a system, it is possible that the model is too complex, or does not allow an analytical solution. In this case, computer simulation can be considered a valuable tool in obtaining an answer to a particular problem. When the model involves random sampling from a probabilistic distribution, the method is called Monte Carlo simulation. The use of Monte Carlo simulation to evaluate measurement data uncertainty is established in the Supplement 1 of the ISO-GUM [5] and is described in Cox et al [6].

Monte Carlo simulation is an automated and wide-ranging tool, since it can be used on nonlinear models, asymmetric distributions of influence quantities, dominant non-normal contributions, correlations between influence quantities, and other difficulties in applying the ISO-GUM classical method need not receive special attention. Furthermore, considerations of the normality of the output estimate and the applicability of the Welch-Satterthwaite formula become unnecessary.

However, the quality of the results obtained will depend on the representativeness of the model and the number of simulations performed [7], which addresses the influence of epistemic uncertainty on the outcomes of the Monte Carlo Simulation.

4. Epistemic uncertainties

Epistemic uncertainties are related to the model limitations on representing the observed phenomena. Its value depends on the level of knowledge possessed during the modeling process.

At first glance, it is tempting to use machine learning or other AI methods to develop degradation models of subsea assets, because of the complexity of the associated phenomena. Petroleum is a complex blend of diverse components, such as oil, water, gas and sand, which flows in pipelines and assets in multiphase regimes. For example, stratified, churn, bubbly, slug and annular flows [8][9].

However, the usage of experimental data to generate statistical or data-driven models presents severe limitations. The amount of available data to build data-driven models is normally insufficient in the oil and gas industry, which has been slowly evolving in the digital transformation of its production process [10], mainly focused on younger fields.

For the majority of the subsea assets, there is a lack of knowledge deriving from the small number of sensors to monitor production variables like pressure and flow, as well as fluid properties, such as oil viscosity, density and sand rate, which are normally measured in laboratories, with a high accuracy but a low sampling rate and reliability. It jeopardizes the performance of data-driven models for degradation of subsea assets.

An alternative is the usage of mathematical or empirical models to estimate the effect of an observed degradation phenomenon on subsea assets. These models use physical or mathematical relationships to relate several production quantities and fluid properties with the observed phenomenon, like erosion rate.

To find these mathematical relationships, test benches are normally used. However, degradation phenomena like erosion and corrosion demand a huge amount of testing hours to be identified, which narrows the amount of data used for model building and validation. Moreover, these bench tests have been normally performed in controlled conditions, with water and air, in ambient temperature and pressure conditions, and steady-state flow regime.

Such conditions contrast with operation conditions, where the production of oil, natural gas, and salt water takes place under high pressure, with unknown flow regimes and unsteady quantities like sand rate. This raises questions about the representativeness of the data used for model development and validation in comparison to operational conditions.

There are plenty of mathematical or empirical models for erosion in subsea assets in literature [11]. Among the most prominent ones highlight Salama [12], McLaury and Shirazi [13], DNV [1] and Shirazi et al [14]. A comparison of their estimates for the same conditions and experimental erosion, measured after test benches, is presented in figure 1.

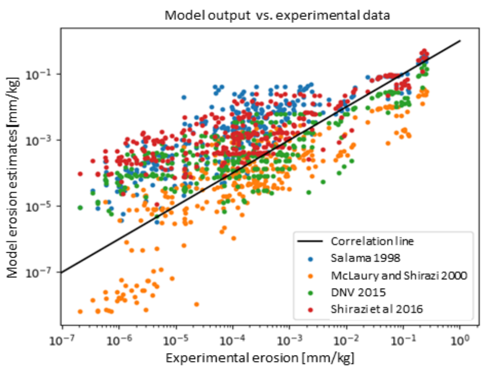

Figure 1. Comparison between model estimations and experimental erosion

It can be seen that the majority of the models estimates present a bias towards conservatism, overestimating the actual erosion rates. It can be understood as a safety issue, relevant when estimating subsea assets degradation. Conversely, it means a lack of reliability of the model, which leads to a high error in the estimates in order to avoid catastrophic failures.

The DNV erosion model presents applied models for the most relevant geometries related to fluid transport in the process industry, very common in subsea oil and gas production systems. The document stands out for the quality of its models in comparison to the state of the art found in the literature, while presenting less conservatism and a detailed procedure for implementing and applying the models.

DNV-RP-O501 presents 12 gas/liquid flow erosion tests, performed in different conditions, which DNV uses to assure the reliability of its models. Although it can be considered a low amount of data, the percentual errors can reach high levels, as shown in figure 2 [1].

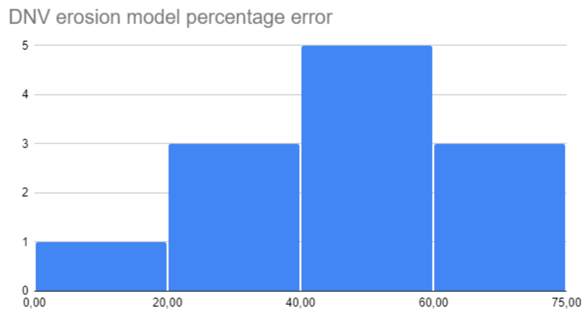

Figure 2. DNV erosion model variations

As presented in DNV-O501 [1], the mean error of the estimates of the DNV erosion model is 44.2% of the measured value, and can vary between 4.5% and 75%. Thus, it is notable that the epistemic uncertainties play an important role in the reliability of subsea assets degradation models.

Important to say that there is no information about the influence of aleatoric uncertainty on DNV results.

5. Conclusion

This article aimed to analyze the influence of uncertainties on the outcomes of degradation models for subsea assets. Focusing on the DNV erosion model, both aleatoric and epistemic related uncertainties were addressed.

The aleatoric uncertainty is associated with the variation of input data. It can be evaluated with simulation methods like Monte Carlo Simulation. The reliability of the outcomes depends on the quality of data and its pre-processing.

The epistemic uncertainty is related to the degree of representativeness of the model in relation to the observed physical process. According to DNV-O501, the DNV erosion model estimates can present errors around 75%, which could mean a low level of reliability [1].

Conversely, this uncertainty level arises from a high level of conservatism and the absence of a suitable amount of test data to perform a correct uncertainty evaluation. Moreover, there is no information about the influence of aleatoric uncertainty within the estimates present on DNV-O501, which could be significant, because of measurement uncertainty and process variations.

Then, the use of epistemic uncertainty in erosion evaluations according to the DNV erosion model demands careful consideration. If the long term variations of the input data are not significant, there is a high probability that a relevant part of epistemic uncertainty has a systematic behavior, which could be corrected.

On the other hand, although uncertainties around 75% could be considered too high, they express the level of knowledge of a complex phenomenon, in a very harsh environment. In other words, although the uncertainty level could be high, the capacity of determination of its value establishes the reliability of the estimates.

The shorter the estimate plus its uncertainty to the asset safety wall width limit, the higher the risk of failure of the asset. Then, the decision of inspecting (or not) a subsea asset is associated with the acceptable risk level. Although the risk of a failure can not be eliminated, it can be kept below an acceptable limit, which drives the decision-making of whether to inspect or not, and when.

In this sense, considering the uncertainty associated with the DNV erosion model improves its trustworthiness, as well as the reliability of the decisions based on them. The consequence of a high level of uncertainty is the decision to inspect earlier than expected, but it is only possible because of the estimates of degradation and its associated uncertainties.

Thus, the use of digital models is much recommended for integrity management of subsea assets. Although the associated uncertainties can be high, the knowledge about the observed phenomenon could be evaluated through inspections, which can be used to improve the reliability and to reduce the level of uncertainty associated with the DNV erosion model.

Next works are going to address issues related to the aleatoric uncertainty and tolerability ranges associated with the acceptable risk level.

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