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Coupling Subsea Asset Risk Based Inspection to Logistic Optimization

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Abstract

Ultra-deep-water exploration and production of oil and gas require the installation of complex subsea assets such as flexible risers, flow lines, manifolds, well heads, etc. The structural integrity of these assets is monitored through a costly repetitive inspection process that involves a fleet of remote operated vehicles (ROV) and ROV supply vessels (RSVs). Risk-based inspection (RBI) can be applied to partially mitigate some of these costs. However, there is still room for improvement that links RBI with offshore logistic optimization. This article presents a new methodology that minimizes operating costs and the risk of failure of subsea assets involved in the O&G industry. A discrete event simulation (DES) model is used to simulate the supply vessel fleet and inspection operations, while an RBI model assesses the risk of failure of subsea assets. Variations of the variables of interest are systematically altered to find the best solution. The results show great potential to reduce costs while maintaining the structural integrity of the equipment. In parallel, the model may provide interesting information on optimal fleet size, chartering contract types, and the best inspection strategy for a specific offshore field. The coupling of RBI with logistic optimization seems promising to improve the efficiency of inspection and monitoring of O&G subsea assets in Brazil.

1 Introduction

As a result of the expansion of oil and gas exploration in deep waters, several subsea elements are used to carry out this activity. Among all the processes involved, including installation and operation, maintenance is one of the most important, as it must be carried out during the useful life of the elements, with the intention of mitigating the potential risks of damage to human life, the environment, and commercials. However, it is a costly, time-consuming and complex process.

The choice of the periodicity of inspections of these equipment is based on several factors and different approaches. A possible strategy is to adopt the RBI (risk-based inspection) technique, with the objective of reducing and optimizing this operation, in addition to assisting in decision making.

Each subsea element inherently has its own risk of failure probability, which can depend on several factors, from where and when it was installed, the type of equipment, among others. This failure probability evolves over time according to several parameters and in a highly nonlinear way, making it difficult to approach by classical means of optimization.

Another challenge is the choice of inspections themselves. Each type of equipment, for technical reasons, can only admit certain types of inspection; and among them the cost and efficiency vary. In this context, it is said to have great efficiency when it leads to a great reduction in the risk associated with failure of the equipment, which would translate into a high fall in the risk curve. For example, visual inspections are milder and less costly, so they do not have much influence on the long-term credibility of the risk curve of the inspected element. Inspections are more detailed and therefore have a greater influence in reducing the risk curve, but are more costly.

Therefore, there is a great logistical challenge associated with this industrial operation, which can be of great benefit by optimizing your inspection and maintenance processes, as well as reducing costs, without compromising safety at work.

This optimization process can be performed using discrete-event simulation with the construction of a model capable of reproducing the real operation digitally (digital twin).

1.1 Bibliographic review

The RBI technique is studied by researchers around the world, from the creation of an RBI planning method for corroded submarine pipelines (Seo, et al., 2015), to the creation of a methodology for RBI of oil and gas pipelines based on fuzzy logic networks (Singh & Markeset, 2009), to the combination of RBI with artificial intelligence to determine the optimal inspection interval in pipelines that suffer corrosion (Abubakirov, Yang, & Khakzad, 2020).

The optimization of pipeline maintenance is also a topic that has been studied for a while. A multilevel optimization maintenance model was presented by synthesizing a Markov corrosion process and multilevel maintenance strategy (Liu, Zheng, Fu, Ji, & Chen, Multi-level optimization of maintenance plan for natural gas pipeline systems subject to external corrosion, 2018) while Bayesian networks and the genetic algorithm were applied to develop a framework for the inspection decision making for corroded pipelines (Liu, Zheng, Fu, Nie, & Chen, Optimal inspection planning of corroded pipelines using BN and GA, 2018).

The development of simulations of subsea production systems has also been carried out. To simulate the configuration of an entire deep-sea production system, a simulation was developed and analyzed that can logically simulate oil production processes in the deep sea (Woo, Nam, & Ko, 2014).

Additionally, Lucas et al. performed a logistic analysis of the inspection of risers and subsea structures. Its objective was to analyze the costs of underwater structure inspection logistics through computer simulations considering inspection frequency, the number of available vessels and the sea and its limitations for several possible scenarios (Rodrigues, Monteiro, & Caprace, 2018). This work can be expanded and improved with the inclusion of IBR, since in the article described the inspection frequency is given by probabilistic data.

1.2 Objective

The main objective of this study is to develop a simulation-based model of subsea inspections based on asset risk regarding offshore transportation, considering stochastic effects of weather conditions on the system. The output of the simulation is the composition of the fleet, the periodicity of inspection, and the costs involved.

2 Methodology

To model the problem, an offshore area with one or more oil extraction wells, each with its own set of equipment, is considered.

The inspection call contracts that can be signed are divided into two categories: a short-term one, specific for a trip, more expensive; and a long-term one, which can cover all the time analyzed, with a reduced price.

Each piece of equipment (excluding risers) has a characteristic risk curve associated with it that evolves over time. Furthermore, given the nature of the process, two levels of risk are also inherently associated: a medium-risk level, referred to as the alarm level, and a high risk, referred to as the imminent failure level.

The alarm level characterizes the minimum risk associated with an inspection request. Although the risk is acceptable at this time, a near future inspection is necessary to verify the real situation of the equipment or perform routine maintenance.

The level of risk of imminent failure characterizes the risk of an unacceptable level for an equipment. At this time, the equipment can trigger a fault at any time and, therefore, it is no longer acceptable. For modelling purposes, some equipment crossing this level would be considered a breach of boundary conditions and therefore this scenario should be considered a failure.

In addition to these two risk levels, a third virtual level is also considered for modelling. This virtual level has no practical representation and exists only as a strategic decision-making mechanism. It can acquire any positive risk value equal to or less than the alarm level and is shared by all equipment. Through it, it is possible to group equipment in similar risk situations, as long as they have the same type of inspection. Therefore, it is used as a parameter for the simulation of the operation. Despite this, the virtual level does not generate inspection requests, only the alarm level.

Risers configure a special group of equipment that does not have naturally associated risk curves, having only routine preventive maintenance plans with variable periodic inspection frequency. Thus, they are still modeled as routine events, as they impact the consumption of logistics assets and the final cost.

Pipelines with different types and severity of defects found at the time of inspection lead to different variations of the defect in the future and different probabilities of failure, making it more reasonable to apply different re-inspection intervals depending on the health conditions of the pipelines themselves.

Other factors still considered include the cost of chartering the ship, based on the price of fuel (diesel) over time, the cost of stopping production, and sea conditions. For the latter, the safety standards established by organs and competent bodies are followed in such a way as to take into account the good and bad weather at the moment of the inspection. In this case, the inspection process is carried out under favorable weather conditions. However, the ship still sails despite the weather conditions. Sea conditions also influence the average speed of the ship, since different times of the year lead to different conditions of tide, wave, and current, which influence the speed of its operation.

The cost of chartering the vessels, the value of diesel, and the value of Brent oil throughout the simulation time were estimated from an extrapolation using the geometric mean reversion (MRM) model from historical data. Mean reversion movements can better describe several variables that tend to a long-term equilibrium level.

The Dixit & Pindyck model is defined as a single-factor geometric MRM, in which an additional variable P appears in each term on the right-hand side of the Ornstein-Uhlenbeck process equation (Dixit & Pindyck, 1994). By this expression, there is a geometric process in which the increment of the variable's value (dP) becomes proportional to the level of the variable itself (P):

$$dP = \eta * (\underline{P} - P) * P * dt + P * \sigma * dz \qquad (1)$$

Being:

- P: stochastic variable,
- $\underline{P}$: Long-term average of the stochastic variable, that is, its long-term equilibrium level,
- η: Velocity of reversion, or the measure of intensity with which stochastic shocks are dissipated by the mean reversion effect,
- σ: Process volatility, or the measure of intensity of stochastic perturbations of the variable,
- dz: Standard Weiner process, with normal distribution: dz=ε√dt, e: ε~N(0,1), and
- dt: process time increment.

The mean and variance expressions of a stochastic process are important for their use in the evaluation. These were estimated from the historical database obtained.

To simulate the process in question, it is discretized into an equation. This is obtained by adding the deterministic part of the mean to the stochastic part, which is then multiplied by the normal distribution with mean 0:

$$P_t = exp\{q_3 + ln(P_{t-1}) * q_4 + q_5 * N(0,1)\} \qquad (2)$$

Where:

- $q_3 = \left(ln(\underline{P}) - \frac{\sigma^2}{2*\eta*A}\right) * (1 - e^{-\eta A \Delta t})$
- $q_4 = e^{-\eta A \Delta t}$
- $q_5 = \sigma * \sqrt{\frac{1-e^{-2\eta A \Delta t}}{2\eta A}}$
- $A = \frac{\underline{P}}{ln(\underline{P})}$

Thus, it is possible to assemble the equations that will govern the time series of charter values, diesel and brent oil in a stochastic way.

RBI data are received and transformed so that they can be read by the simulation algorithm together with all other input, such as weather, field, and vessel data, as seen in Figure 1.

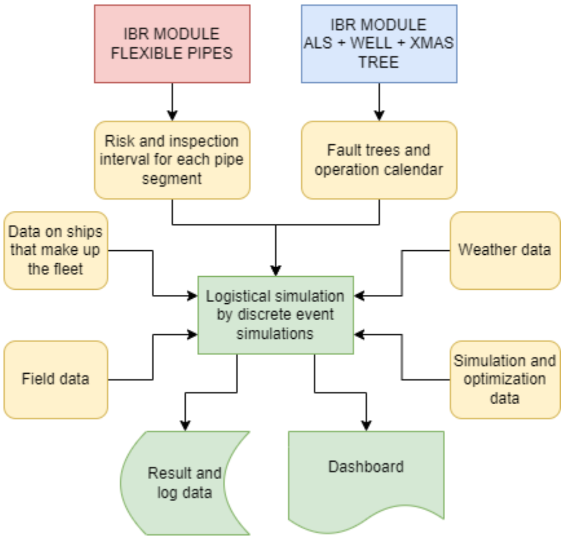

Figure 1 - Simulation input and output flows.

We can model the total cost of the operation as a function such as

$$C_T = \sum ct + \int cd(t)dt + c_{pp} \quad (3)$$

Being:

- C_T: total cost of operation,
- ct: contract cost,
- cd(t): Function that describes the fuel cost of the entire fleet over time,
- c_{pp}: Production stop cost.

The fuel consumption per hour of the vessel is affected by its operation, which means that if the vessel is sailing, its fuel consumption is higher, but if the vessel is in anchorage or doing an inspection, its fuel consumption is lower. Fuel consumption during inspection is influenced by how long the inspection is, so different equipment takes different time to inspect.

The inspection time using ROV is a function of the depth and length. The ROV has its own vertical and horizontal velocities, so the deeper and longer the equipment, the longer the inspection time.

It is important to mention that the model is developed in a parametric way so that it can be executed using different combinations in an iterative way and always compared with previous executions, with the objective of reaching the optimum.

In the present study, we want to obtain the optimal parameters that lead to minimizing the total cost of operation (fuel costs and charter contracts for inspection) and minimizing the total risk over time. It is, therefore, a multiobjective problem, and trade-offs are expected to be posthumously considered.

The simulation is then used by an external multi-iteration algorithm, with the final objective of obtaining a minimum-cost scenario that never allows any equipment to exceed the higher risk limit, the danger of imminent failure.

2.1 Assumptions

- Earth's curvature was not considered in navigation.
- Vessel speeds are constants through simulation only being affected by weather.
- The vessels are considered immediately available.
- Alarms are defined before running the simulation and fixed throughout it.
- Continuous functions are discretized from a sampling rate equal to the simulation step, which implies the accuracy of the model.
- The dynamics involved in each of the inspection processes are not considered, approximating their durations by a consistent statistical distribution.
- The spot contract is 25% more expensive than the long-term contract.

2.2 Scenario Description

The simulated scenario consisted of evaluating the risk-based inspection of 6 systems plus 5 regions of 6 flexible pipelines with at least two RSVs available for 36 years.

The weather and the distance to be traveled influence the fuel cost of the vessels. Therefore, a Traveling Salesman algorithm is executed whenever an inspection list is formed containing the systems that have crossed the virtual alarm line and the flexible pipes that are in the inspection period to ensure that the vessels sail the least.

The cost of the vessel was estimated for both the Spot contract, that is, the one signed whenever a service is needed, and the long-term contract signed from the beginning of the simulation to the end. The cost of stopping production for inspection is also considered (loss of production).

Before every beginning of service, the vessel first travels to port to load fuel. This loading time was considered to be the triangular distribution of 3 days with a variance of 1 day.

3 Results

Figure 2 shows the vessel cost curves over time for the first iterations of the scenario execution.
The cost of Spot and Long contracts is analysed simultaneously in order to help the user assess which one is cheaper for the scenario.

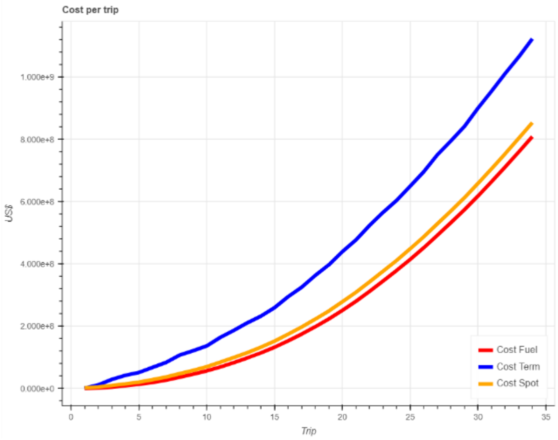

Figure 2 - Cost of the vessel over time.

It is easier to see that the Spot contract was cheaper. This happened because the first vessel stayed at Anchorage for 92.1% of the simulation time, as seen in Figure 3, which led to 7.75% of the vessel usage. The second vessel stayed in Anchorage for 99.7% of the time, which led to 0.29% of its usage.

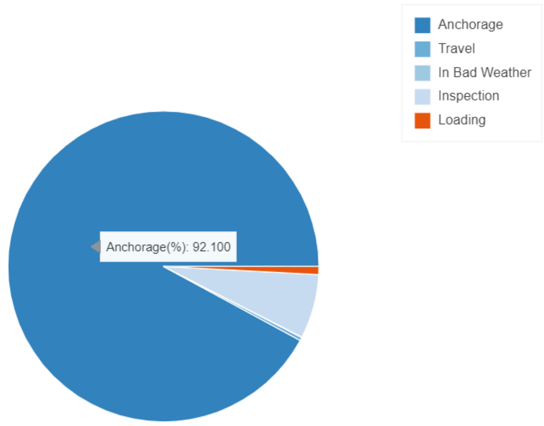

Figure 3 - Analysis of the vessel usage time.

The total cost of the simulated scenario after 200 iterations with a frequency variation of 360 hours and the use of up to 2 vessels can be seen in Figure 4. Note that there is a discontinuity in the lines, which indicates that some iterations were interrupted due to equipment failure. For that, an example value of the failure limit of $3*10^{-1}$ was considered; however, this value can be changed whenever desired.

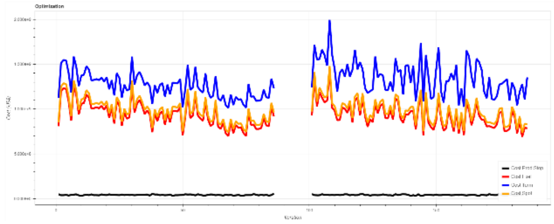

Figure 4 - Multi-iterations results to find an optimum.

According to the data presented, the lowest-cost iteration of the Spot contract is 184. This iteration has both vessels available all the time and includes an increase in the virtual alarm of all equipment of 0.092 points from the baseline of 0.1, 0.2 being the alarm threshold and 0.3 the failure threshold.

4 Discussions

The combination of RBI with discrete event simulations proved to be a good way to assess the cost of vessels performing inspection services and inspection periodicity, helping planners to find the best planning for such activity considering the systems to be inspected.
The simulation can be expanded so that a higher number of systems and ships are considered in order to evaluate different cases from hypothetical to the optimization of real cases.
The results may also be used to help oil and gas companies to better optimize their service contracts sharing the services between several oil fields.
That being said, this evaluation can be expanded with the use of automatic optimization such as Genetic Algorithms, which will help planners find the optimal combination of vessels and inspection periodicity automatically to prevent equipment failure, minimize costs, and avoid incidents.

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