Pipeline integrity and extending marginal system life using machine learning algorithms.

1. Abstract

The condition of critical oil and gas infrastructure deteriorates with age. This can be due to a number of reasons, for example time-dependent degradation mechanisms such as corrosion or fatigue. Pipelines are expensive assets and the change in risk of failure due to degradation can affect the whole economics of operating the asset.

The authors of this paper have applied structural reliability techniques to large numbers of defects on aging assets, this methodology can take time and can become computationally expensive using traditional Monte Carlo simulation.

For this reason, the authors have trained machine learning algorithms to categorise defects by their probability of failure. The population of defects having a high predicted failure probability were selected for probabilistic assessment first, followed by the lower probability populations. Categorisation of defects in this way enabled the authors to improve the efficiency of the assessment process.

By using a blend of custom designed assessment and machine learning software the authors have developed a cost and time efficient method of assessing the risks associated with the life extension of existing assets.

2. Introduction

The larger fields on the United Kingdom Continental Shelf (UKCS) are in general approaching an age where the infrastructure and, the export pipelines are required to continue to operate well beyond the original design life.

Smaller pools of hydrocarbons are being discovered, these smaller pools can only be economically exploited if existing processing and export infrastructure remains economically feasible to maintain and to operate to acceptable standards of safety.

Recent exploitation, or proposals for exploitation of smaller fields such as Orlando, Vorlich and Harrier rely on nearby processing and exportation infrastructure. In all probability these fields would not be economic to develop individually. The Oil and Gas Authority (OGA) have previously stated that there are in the region of 200 smaller pools of hydrocarbons which lie close to existing infrastructure. [1]

The UKCS is undergoing a transition from Exploration Led Assets (ELA) to Asset Led Exploration and Exploitation (ALEE). Fields developments such as the Greater Stella Area show that beneficial exploitation of smaller pools can be achieved by utilising pre-existing exportation infrastructure.

Recent legislation requires operators on the UKCS to maintain and operate their infrastructure in a way that maximises economic recovery. It is important to note that the legislation is not owner/operator specific or related to the original design life, the infrastructure must be maintained and operated in a way which maximises economic recovery of the geographical region and may include consideration of use by others in the future.

The Maximising Economic Recovery (MER) legislation states that:

"Relevant persons must, in the exercise of their relevant functions, take the steps necessary to secure that the maximum value of economically recoverable petroleum is recovered from the strata beneath relevant UK waters." [2]

The ability to prove that a pipeline is safe for continued use in the future has strategic implications for development of smaller pools and helps provide justification that assets are managed in a such a way that maximises economic recovery.

3. Determining a pipelines' continued suitability for use.

Assessments currently performed to determine if a pipeline is suitable for continued use can be split into three categories, the categories are deterministic, probabilistic and semi-probabilistic.

3.1. Deterministic Assessment

The deterministic assessment uses extreme variable parameters such as the specified minimum or maximum for each parameter, this approach provides conservative results given conservative assumptions. Each defect is assessed using one calculation iteration which requires low resource and computing requirement, which in turn results in a low cost, at the expense of a conservative assessment.

More advanced methodologies such as probabilistic and semi-probabilistic techniques can be used to reduce conservatism, and to provide a direct probability of failure. In both cases a high degree of competence is required by the engineers performing the task and the techniques diverge considerably in the required computing resources.

3.2. Probabilistic Assessment

One method of Structural Reliability Analysis (SRA) is Monte Carlo Simulation (MCS). Distributions of parameters are derived from measured data, for example input variable distributions for yield and tensile strengths can be constructed from mill test certificate data.

The MCS will perform many iterations using a different value for each iteration in accordance with the distribution curves generated. Each individual iteration can be considered as an individual deterministic assessment; however, each defect assessment will entail performing many individual iterations. Considering the low probability of failure being assessed, this is typically in the region of 1×10^9 iterations which requires considerable computational resources.

3.3. Semi-Probabilistic Assessment

First Order Reliability Methods (FORM) were proposed in the early 1970's as reliability indicators for deterministic systems. The original methodology was proposed by Hasofer and Lind in 1974 [3]. Further developments of semi-probabilistic methods such as Second Order Reliability Method (SORM) as well as FORM have limitations, typically the applicability must be proven by MCS, so the use can be limited.

4. Proposed Assessment Methodology

Traditional probabilistic assessment performed as part of an Aging Life Extension (ALE) study or SRA assessment, is limited by computing power and restrictions on time to delivery of the assessment. Only the worst-case defects are assessed to reduce the resources required, however the worst-case defects are defined using engineering judgement which is open to error.

The authors propose to use advances in modern computer architecture to accelerate the Monte Carlo simulation using parallel processing techniques.

The authors originally proposed the use of machine learning to categorise all defects as having a high, medium and low probability of failure, thereby identifying high risk defects for further assessment. As explained in Section 6, a data entry process has been identified which allows direct assessment and prioritisation using an estimated probability of failure.

The resulting process results in a systematic way to identify and assess the defects at higher risk of failure in a cost, time and resource efficient manner. This provides end-users a high confidence in results.

4.1. Core Assessment Criteria

The core assessment criteria uses internationally recognised criterion such as the ASME Modified B31.G [4], Kastner [5] and Battelle NG18 criteria [6].

4.2. Machine Learning and Artificial Intelligence

Machine Learning (ML) and Artificial Intelligence (AI) are related but differ in the way the output is manipulated. ML uses statistical categorisation methods and supplied training data as part of a supervised learning process to output the answer which most closely correlates with the statistical relationships of previously processed learning data. AI attempts to use the output of ML to return an output or perform a task which could also be characterised by human intelligence.

4.3. Parallel Processing

MCS consists of many, typically simple calculations, the high computing resource cost is a direct function of the large number of iterations required (typically 1×10^9).

The Central Processing Unit (CPU) of a computer works in a simple linear manner, each iteration is calculated before the CPU moves forwards to calculate the following iteration. The authors have developed custom software which uses the Graphical Processing Unit (GPU) to perform the calculation of many iterations simultaneously. The number of simultaneous calculations is limited by the number of processing cores within the GPU and is typically in the region of 768 to 2048 in modern GPU units, albeit at a slightly slower processing speed than the CPU.

5. Parallel processing to accelerate Monte Carlo simulations

The Pipeline Research Council International (PRCI) methodology was chosen as a base methodology for research [7]. The authors recognise that at its core a single assessment is performed, later work by the authors includes addition of other assessment techniques commonly used throughout the pipeline industry.

The MCS process performs many discreet deterministic assessments using input variables chosen with a frequency determined by the probability distribution of the variable. In practice this means that many simulations will be performed using a value nearest to the variable mean value, and fewer simulations using the extreme values.

For most iterations the deterministic assessment will not result in a prediction of failure, only in the cases where several independent improbable variable values occur simultaneously will failure be predicted. If insufficient iterations are performed the combinations of values which result in an assessment failure may never be assessed. When insufficient iterations are performed the likelihood of underestimating the probability of failure is greater than the probability of overestimating it.

Shooman's equation [8] (Equation 1) shows that for a typical MCS, the number of iterations must be a further 2-3 orders of magnitude greater than the magnitude of the event being assessed. For example, a 10^{-6} event would require somewhere in the region of 10^8 and 10^9 iterations to return a stable result when assessed at a 95% confidence level.

$$\%S = 200\sqrt{\frac{1-P_f}{NP_f}} \qquad \text{(Equation 1)}$$

Iterations	Time per defect
1.00E+4	1 Sec
1.00E+5	10Sec
1.00E+6	1.7 Min
1.00E+7	16.7 Min
1.00E+8	2.8 Hours
1.00E+9	1.2 Days
1.00E+10	1.7 Weeks
1.00E+11	16.5 Weeks
1.00E+12	3.2 Years

Table 1 - Time taken to assess a single defect by MCS

Early trials using ML indicated that a stable result using ML would require somewhere in the region of 1000 data-points in the failure region, this results in a total requirement to perform approximately 1E+12 iterations and the consequent time requirement as shown in Table 1 for this number of iterations. The authors determined that parallel processing was a viable method to accelerate the number of iterations completed in each time period.

To overcome the computational limitations of processing the iterations linearly using the CPU, the authors re-coded the methodology using the C++programming language and integrating with the CUDA derivation of the C++ language for the CUDA parallel computing platform and application programming interface. This enables multi-core processing using a standard NVidia GPU graphics card commonly used for gaming [9,10]. The resulting processing speed was found to be around 100 times quicker than by using linear CPU computing. The process is improved by a further order of magnitude by using a partial-probabilistic model as detailed in Section 7.1.

6. Machine Learning to Identify Defects at the Highest Risk of Failure

The authors considered methods to identify the defects with the highest probability of failure, and which would require further detailed assessment. Defects in the pipeline at a much lower risk of failure are unlikely to fail first and do not undergo detailed assessment.

Early research conducted by the authors focused on using a ML process trained on a dataset of pre-calculated defect failure probabilities, the ML process succeeded in determining which defects had the highest probability of failure, and therefore excluded many defects from requiring individual assessment.

The results of ML however, are influenced by the training dataset. The authors are aware that by having a training dataset populated by data from defects with a high probability of failure, the ML results are biased in accuracy towards high probability defects. For this reason, caution must be used when adding additional defects to the training dataset, when the defect has previously been assessed as being at high risk of failure.

Initial work with ML used Orange software, [11] later work has been transferred to the C++ language however Orange has a clear graphical interface which is used to illustrate the ML process explained in this paper. An example of a ML training process flow is shown below in Figure 1.

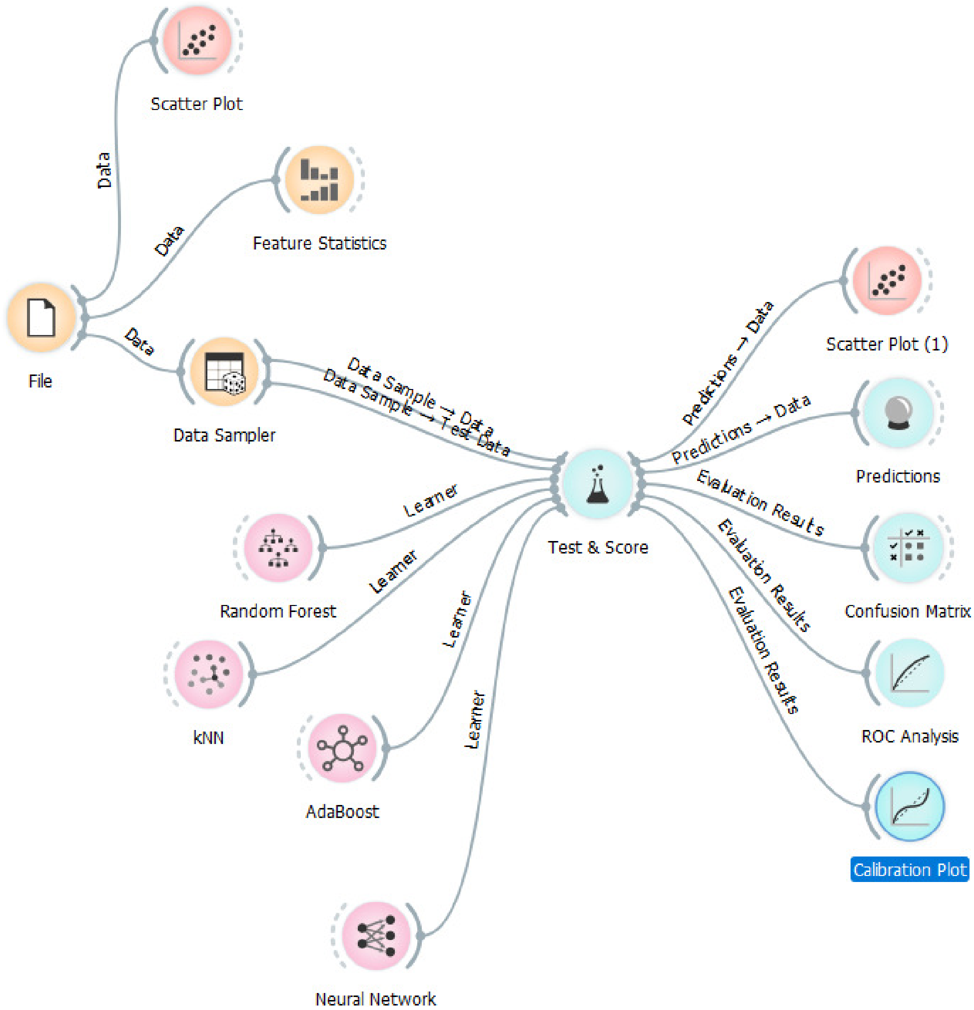

Figure 1 - Typical ML training process flow

Early work in classifying the defects at high, medium and low risk of failure showed that three input variables can describe each individual defect in a specific pipeline, the defects are described using initial length, initial depth and year.

Each defect has previously been assessed using the parallel processing procedure described in Section 5 to compute a predicted probability of failure. The calculated probability is divided into high, medium and low risk of failure to generate target data to train the ML algorithm. The categorisation is illustrated in Figure 2, defects of extreme length exhibit a reduced rate of change in the Folias bulging factor and hence tend towards a common probability of failure that is dominated by depth at further increases in length, this forms an upper-bound to the required lengths of defect to be assessed.

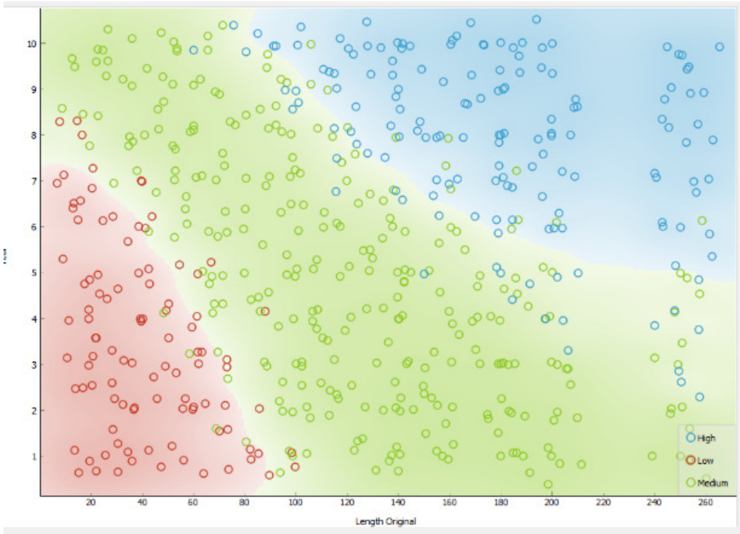

Figure 2 - Correlation of probability of failure with respect to length and number of years

The authors identified that the accuracy of classification of defects using ML was degraded by including the year as input data, the input data the model is trained on is not assigned ranking weights, therefore the year assessed is as important as the initial defect’s size. Where it is recognised that many iterations using MCS will result in a mean value being obtained for the corrosion growth rate it is possible to provide an alternate data input of current length and current width.

The problem described is an example of data quality versus data quantity when using ML processes. By assigning a current dimension under the partial-probabilistic model it is possible to provide ten times as many individual defect dimensions using the same size of input dataset provided by MCS. The result is equivalent to an order of magnitude reduction in computing resources required to perform MCS. The change to the input data improves the accuracy of the ML predictions at no further cost.

An example of output results from the improved ML procedure is shown below in Figure 3, many results are classified correctly, of the remainder 3 defects from the 99 test defects are classified non-conservatively.

Actual \ Predicted	High	Low	Medium	Σ
High	21	0	3	24
Low	0	16	0	16
Medium	2	5	52	59
Σ	23	21	55	99

Figure 3- Example ML classification output

The authors have found that the improved data entry format for ML training has resulted in an improvement in accuracy such that a direct prediction of probability of failure is possible from the ML algorithm. An example of the probability of failure output is shown in Figure 4. The result is neither strongly conservative, nor non-conservative and when repeated for each defect, clearly identifies those defects at increased probability of failure. No further assessment is required where the result is judged to be sufficiently accurate.

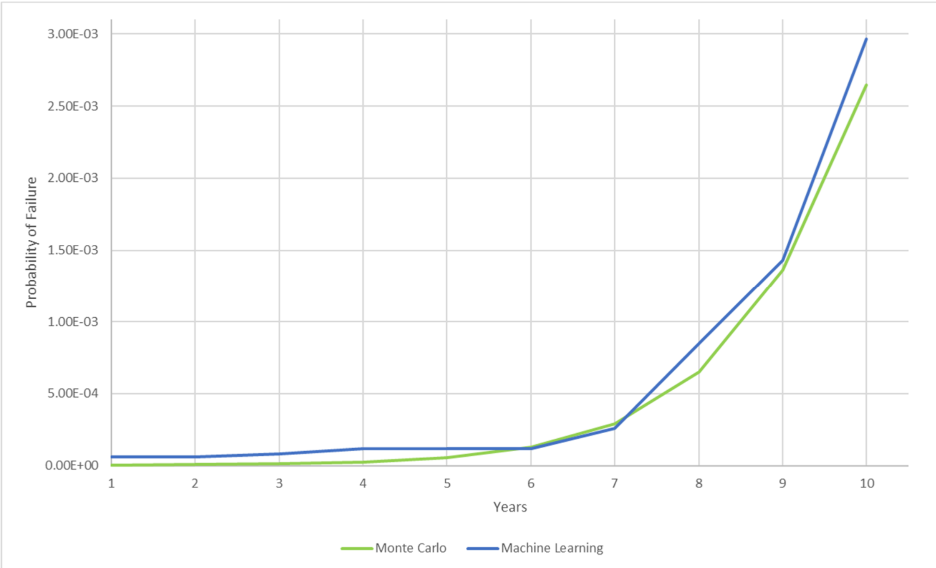

Figure 4- Predicted probability of failure

To use this technique to be able to predict the defect probability of failure at a particular year it is important to recognise two main concepts:

1. The calculated probability of failure is calculated by fully probabilistic MCS.
2. The most probable corrosion growth rate for each year tends to the mean when considered over many iterations, and thus under the partial-probabilistic model for estimation of the failure probability, the most probable defect dimension in each year is directly related to the mean corrosion growth rate.

7. Summary

The authors recognise that structural reliability analysis using Monte Carlo simulation can help demonstrate that pipeline infrastructure is being operated in a way which maximises economic recovery, and that the analysis can be of commercial use when making the final investment decision on the development of smaller hydrocarbon pools which would rely on the continued availability of existing infrastructure.

The use of structural reliability analysis is resource constrained. To reduce resource requirements, the authors propose a partial-probabilistic model that provides traditional probability of failure values.

7.1. Partial-Probabilistic Pipeline Defect Assessment Model

The partial-probabilistic model calculates probability of failure using the fully probabilistic Monte Carlo simulation for a range of pre-determined defect dimensions. This is achieved by the following steps:

1. Performing a Monte Carlo simulation of training data which is accelerated in the region of two orders of magnitude using custom design parallel processing software.

2. Training custom designed Machine Learning software on the MCS data output, using the mean defect dimension at each year to provide another order of magnitude of improvement in speed.

3. Based on an equivalent deterministic corrosion growth rate, defect dimensions are chosen for each year which forms part of the required output. The corrosion growth rate may be changed from year to year; this has the advantage of being able to run 'what if' scenarios such as predicted water breakthrough, at deterministic speeds.

4. The output results can be used directly if of a suitable level of accuracy for the intended task. Alternatively, defects can be fully assessed using the GPU accelerated Monte Carlo simulation.

The authors have shown that Machine Learning and GPU accelerated Monte Carlo simulation using a partial-probabilistic model can be used to calculate the probability of failure of defects in a pipeline in a comparable time to that taken for a single Monte Carlo simulation computed using current methods.

The authors have also shown that the partial-probabilistic model can be used to cost effectively assess 'what if' scenarios at deterministic speeds, which can then be used to optimise strategy and final investment decisions.

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