Accounting for Corrosion Growth and Interaction in Future Severity Assessments

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Abstract

The determination of corrosion growth rates and their application in the prediction of future severity is a critical part of pipeline integrity management. Accurate corrosion growth rates are needed to predict pipeline reliability as a function of time, to identify the need for and timing of field investigations and/or repairs and to determine optimum re-inspection intervals. The consequences associated with both underestimating and overestimating growth rates can be significant in terms of both safety and resource performance.

The use of repeat ILI data to match and compare metal loss sites in order to estimate the corrosion growth rates at individual defects along a pipeline is a well-used and established practice in the industry. There are many ways that corrosion growth rates can be used in future integrity predictions with most approaches only accounting for corrosion growth in the depth dimension taking no account of surface area growth and potential interactions between adjacent corrosion areas over time. Now that we have a wealth of historical data with 3, 4 or even 5 sets of ILI data for the same pipelines we are able to experiment with more advanced three-dimensional modelling and have the ability to test new approaches vs actual "truth" data. With the benefit of this progressive viewpoint, the methodologies employed for evaluating and applying ILI based corrosion rates are being further improved and refined to give more accurate predictions of the future pipeline condition, the response schedule and for setting the timing of re-inspections.

This paper describes a new approach that predicts how an area (cluster) or corrosion could grow over time combining with surrounding corrosion defects and with newly developing defects as well as in the depth dimension. The main differences between this and the more established approaches are:

- It does not use fixed individual defect or pipe spool growth rates, but instead uses a growth rate distribution drawn from a group of corrosion defects under the same or very similar corrosive environment.
- The assessment accounts for growth in all three dimensions (depth, length and width) and models the more complex interaction between nearby areas of corrosion.
- It uses a machine learning model to predict the location and pattern of potential new corrosion sites.

The new approach is illustrated and compared to the more established methodologies via the use of case studies on real ILI data sets.

Introduction

Corrosion is still considered one of the major threats to the integrity of many onshore and offshore, gas and liquid pipelines [1,2]. Corrosion can affect the load carrying capability of a pipeline and, if it is allowed to continue to grow, it will result in either a leak or rupture release when it reaches critical dimensions for the pipeline.

The accurate estimation of the corrosion growth rates in a pipeline is a key consideration in the development of effective Integrity Management Programs [3]. The determination of the need for, as well as the location and timing of mitigative or preventive measures such as CP upgrades, coating repairs, pipe repairs and chemical treatment programs for pipelines carrying corrosive products all

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depend on assumptions about the rate of corrosion growth. Also, decisions on the re-inspection interval for the pipeline need to consider the remaining life of the unmitigated corrosion defects remaining in the line.

Many pipelines have now been inspected using intelligent in-line inspection (ILI) tools several times. Using these repeat ILI data sets to determine corrosion growth rates is now an established and recognized best practice with pipeline operators [4-7]. This paper shares some of the experience gained and the improvements made to the determination of corrosion rates from repeat ILI surveys. It is also discussed how the derived corrosion rates can be applied in a pipeline integrity assessment to give accurate predictions of the future pipeline condition, the response schedule and for setting the timing of re-inspections. These topics are illustrated and investigated via the use of case studies on real ILI data sets.

Methods of Estimation Corrosion Rates

The determination of where corrosion is active and how fast it is growing is a complex process which is highly variable and difficult to predict due to the localized nature of corrosion and the many parameters that influence the corrosion reaction.

For internal corrosion the parameters that influence growth rates include corrosivity of the transported product (CO2, H2O, H2S, use of chemical treatments etc, content), temperature, pressure, flow rates, presence of solids, presence of microbial conditions, topography etc. Internal corrosion growth can be measured using in line probes and coupons. However, the results are highly dependent on the placement of the probes and coupons in the pipeline and can only provide average growth rates for general corrosion. Various predictive models exist to estimate corrosion growth rates in 'sweet' oil and gas pipelines using operating data. These predictive models are either purely empirical (field experience) or semi-empirical (based on laboratory data, corrosion rate data etc.). They tend to be complex to use, require many inputs and generally return maximum, worst-case estimates.

Unlike internal corrosion, which occurs in a closed system, the rate of the external corrosion reaction is influenced by many different environmental factors including coating breakdown, cathodic protection (CP) failure, soil type and water content, pH, resistivity, presence of microbial conditions, degree of oxygenation, temperature etc. [8,9] Therefore the prediction of external rates is even more complex and there is currently no widely used method for estimating corrosion rates using empirical equations. As there are so many parameters that influence the external corrosion process corrosion tends to be quite localized and often occurs in "hot spots" (where the rates may be higher than other locations). Consequently, the prediction of where external corrosion will occur in a pipeline and the associated growth rates is a complex and highly variable problem.

Since the general introduction of in-line inspection (ILI) techniques in the 1980's and the broad adoption by most operators by the 1990's/2000's (for transmission pipelines at least) ILI has become the commonly used method for determining where on a pipeline corrosion is occurring and the dimensions and by inference the severity of the corrosion [4-7]. The advance of technology in this field has resulted in the availability of many types of ILI technology to cater for the large range of pipeline sizes, product types, internal restrictions, the different forms of pipeline defects that can occur and the on-going demand to categorize defect types and predict dimensions more accurately. When there is more than one ILI run for estimating the corrosion growth rates it is now

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commonplace to compare the two ILI defect populations in order to estimate the rate of corrosion growth based on defect-to-defect matching. The significant advantage over other methods is that ILI can provide size and growth rate information on the whole detectable defect population giving visibility of what is happening along an entire pipeline.

For pipelines with successive ILI runs the detected population of corrosion defects can be compared to identify both internal and external corrosion growth. Depending on the number of defects to be compared, the assessment can demand significant effort and expertise to ensure accurate and meaningful correlations between often very large ILI data sets. Specialist ILI comparison software facilitates efficient and accurate defect-to-defect matching and the depth comparison to determine the defect specific growth between the two runs across the large ILI defect populations.

However, since ILI as a measuring technique is subject to inherent uncertainties [6], the prediction of corrosion rates from consecutive ILI runs also has a degree of uncertainty. The Signal matching technique is the most accurate method of comparing repeat ILI data sets as it reduces both the data matching errors and the growth measurement error. The growth measurement error is reduced by a direct comparison of the ILI signals and the use of signal scaling or calibration techniques (bias is eliminated and repeatability error is much smaller than the measurement error associated with the individual two tool runs). The use of a signal matching method will maximize the accuracy of the resulting corrosion growth rates.

Application of Corrosion Rates in Future Severity Predictions

There are many ways that corrosion growth rates can be used in future integrity predictions [9,10] with most approaches only accounting for corrosion growth in the depth dimension taking no account of surface area growth and potential interactions between adjacent corrosion areas over time. Areas of corrosion which are reported by ILI data analysis as “clusters” will change over time in all three dimensions (depth, length, and width dimensions) as the existing sites grow and new corrosion sites occur in and around/adjacent to the edges of existing areas. It is the depth and axial length dimensions that are the key measurements influencing the burst pressure prediction of an area of corrosion when the hoop stress is dominant [11]; in rarer scenarios where an axial stress is dominant (for example in areas of ground instability) the depth and circumferential (width) dimensions can become the burst pressure drivers. Two or more corrosion sites that are not touching but are close enough to interact (i.e., have a lower burst when treated as one feature vs treated as individual features) should be considered as the same area for the purposes of pipeline integrity calculations. This is handled by the ILI analysis clustering rules applied when reporting areas of corrosion, i.e., the clusters. However, when predicting future integrity of a pipeline it is the existing cluster surface dimensions (at the time of the last ILI run) that are used with typically only the depth dimension being increased by the observed corrosion growth rate.

Over time we have gathered a lot of historical ILI data and with 3, 4 or even 5 sets of ILI data for the same pipelines we are able to experiment with more advanced three-dimensional modelling and can test these new approaches vs actual “truth” data. A new approach has been developed that predicts how an area (cluster) of corrosion can grow over time allowing it to combine with other surrounding corrosion defects and with newly developing corrosion. This new approach is called Runcom™ Cluster Growth 3D (RCG3D) and the main differences between RCG3D, and the more established (depth growth only) approaches are:

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- The new RCG3D approach does not use fixed individual defect growth rate or pipe spool growth rates, but instead uses a probabilistic simulation model to select rates from a distribution.
- The growth rate distribution is derived from a group of corrosion defects expected to be under the same or very similar corrosive environment.
- The probabilistic model is used to run multiple simulations across the groups for a specified reference period[1], for each simulation a burst pressure is calculated and the set of growth rates (one rate for each individual metal loss box) is stored. The results are ranked based on highest to lowest burst pressure and the set of growth rates corresponding to the 95th percentile and 50th percentile burst pressure values are selected.
- The RCG3D assessment accounts for growth in all three dimensions of the individual defects (depth, length, and width) and models the potential for future interaction between nearby areas of corrosion via a machine learning neural net model to predict plausible sites and patterns of new defect initiation (more information on the development of this model are provided below).

Prediction of New Corrosion Sites Using a Machine Learning Model

The machine learning model used to predict new corrosion sites is a convolutional neural network trained on areas of ILI data where new feature initiation was observed between inspection runs. The training data input was both the location of existing corrosion features and the ILI signal data, and the output target used was the location of any new corrosion sites. The model was trained across thousands of corrosion areas in multiple pipelines showing varied patterns of corrosion initiation. Utilising the ILI signal data in relatively large areas was found to be important to model performance as this provides the model with the spatial relationship between new and existing corrosion sites within the context of the surrounding corrosion and includes any subtle indications of possible low-level corrosion below the detection and reporting specification of the ILI tool.

The final model exhibited a good overlap between predicted and actual new corrosion areas on validation data using an F1 score metric[2], although in practice the model is not expected to accurately predict the location of new corrosion sites, but rather to add new features in statistically likely and realistic areas. When these are included in the growth modelling scenarios and interact with existing corrosion the methodology will highlight corrosion areas where the addition of new features will more significantly affect the severity.

An illustration of the model's output is shown in Figure 1. Each of the examples have four images which show:

- The ILI signal data from the first inspection run. This is part of the input to the model (**Previous Image**)
- The ILI signal data from the second inspections run including the new corrosion features (**Latest Image + h.m**)
- The actual location of the new features (**Heatmap Expected**)
- The model's prediction of the new features locations (**Prediction**).

[1] The reference period is usually set as the intended time interval before the next ILI survey is ran.
[2] The F1 score metric is a statistical measure of predictive performance.

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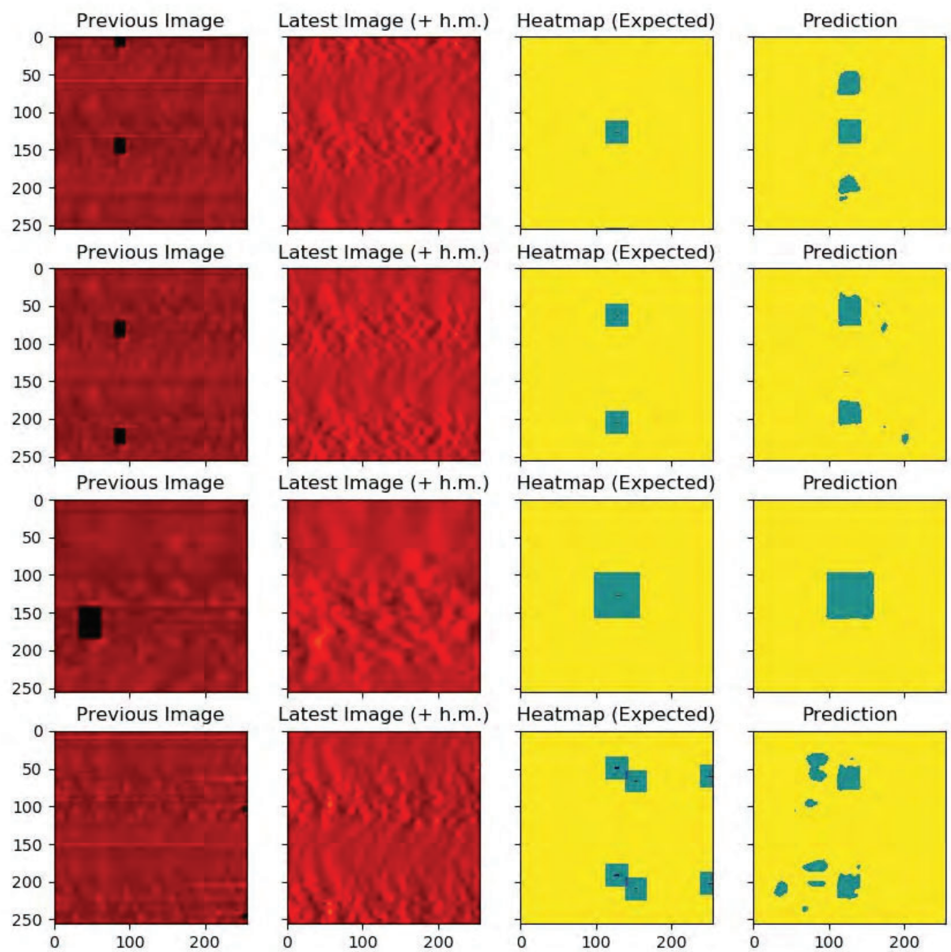

Figure 1: Example of new corrosion site prediction

The new RCG3D approach is illustrated and compared to other commonly used methodologies via the use of case studies on real ILI data sets in the following sections.

Case Studies

The new RCG3D approach is illustrated below via the use of case studies on a real ILI data set. The details of the ILI datasets used in this case study are as follows:

Construction details:	X52 LSAW pipe in mid-1980's
MAOP:	72% SMYS
ILI runs (metal loss):	2022 (2019, 2016, 2012...)
Ext Metal loss Cluster Count:	Approx. 5,000 (>10%wt in 2022)
Deepest Cluster:	56% wt (in 2022)
Max Growth Rate:	0.6mm/yr (24mpy) (2022 – 2019)

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Figure 2 shows the severity (calculated burst pressure) of the reported metal loss clusters (based on the ILI reported 2022 dimensions) assessed using the RStreng methodology. None of the metal loss clusters require an immediate response; the lowest burst pressure ratio (FPR[3]) value is 1.3 (i.e., it is above the selected 1.25 safety factor for this assessment) and no clusters exceed the 80%wt maximum depth criteria.

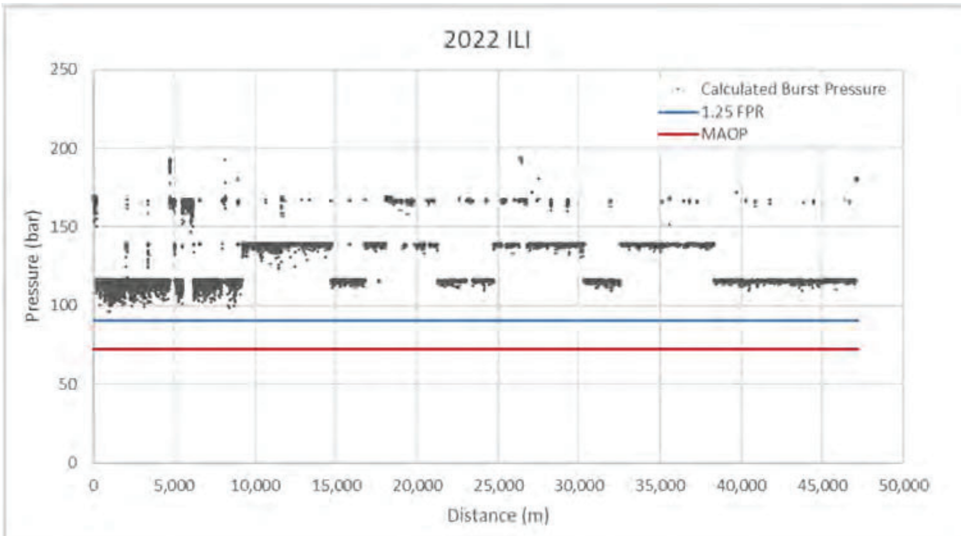

Figure 2: Sentenced Plot of the 2022 ILI Metal Loss Clusters (using RStreng)

Figures 3a. to 3f. that follow below show the projected FPR values along the length of the line using growth predictions representing i) the 95th percentile "worst case" scenario and ii) the 50th percentile "expected case" scenario at time intervals of +3, +7 and +10 years following the 2022 ILI run.

These charts show how the predicted burst pressure for each cluster decreases over time for the two different growth rate scenarios. The reason for calculating both the 95th and 50th percentile scenarios is to provide additional flexibility in the use of the RCG3D approach beyond the usual safety factors applied to the predicted burst pressure (via a FPR limit). A limit is also applied to the predicted increase to the cluster peak depth over time; a peak depth limit of 80% wall thickness is applied in this case study (this value can be lowered if required).

[3] FPR – Failure pressure ratio (ratio of the predicted burst pressure to the maximum allowable operating pressure (MAOP))

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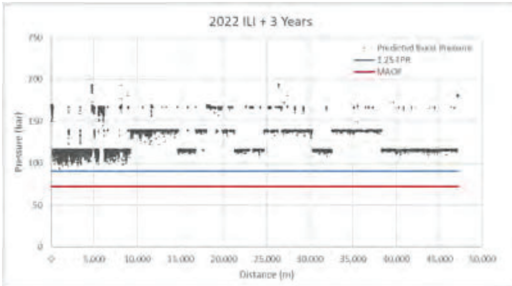

Figure 3a. FPR Values After 3 Years (95th percentile)

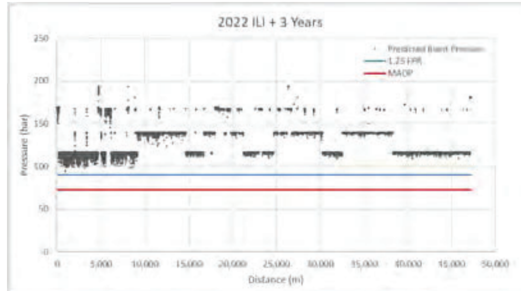

Figure 3b. FPR Values After 3 Years (50th percentile)

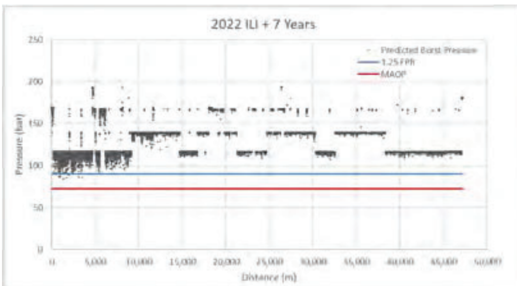

Figure 3c. FPR Values After 7 Years (95th percentile)

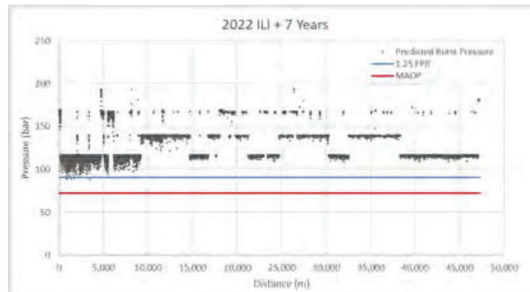

Figure 3d. FPR Values After 7 Years (50th percentile)

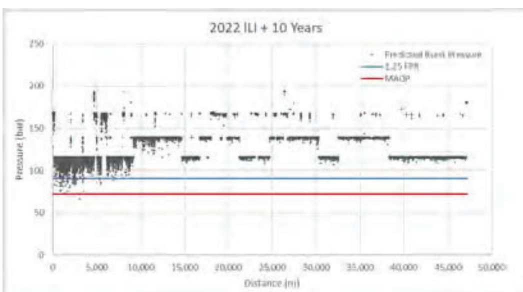

Figure 3e. FPR Values After 10 Years (95th percentile)

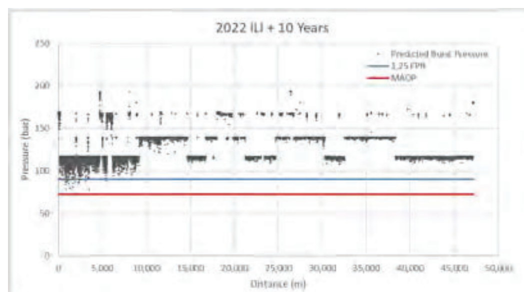

Figure 3f. FPR Values After 10 Years (50th percentile)

Table 1 below shows the number of clusters that would infringe the allowable FPR (<1.25) and/or the peak depth (>80%wt) criteria for the two scenarios ("worst case" and "expected").

Scenario	Criteria	2022 + 3 years	2022 + 7 years	2022 + 10 years
95th percentile "worst case"	FPR <1.25	0	9	47
	Peak Depth >80%wt	0	1	1
	Total	0	9	47
50th percentile "expected case"	FPR <1.25	0	4	26
	Peak Depth >80%wt	0	0	0
	Total	0	4	26

Table 1: Number of Clusters Exceeding the Allowable FPR (<1.25) and/or Peak Depth (>80%wt) Criteria.

All the clusters predicted to exceed the pressure and depth criteria are in the first 7kms of the pipeline. This is consistent with the distribution of growth rates observed between the 2019 and 2022 ILI runs (see Figure 4 below). It is highlighted that most of the population of metal loss defects did not show any material growth between 2019 and 2022; 95% of the calculated rates are below 0.14 mm/yr (=5.5 mpy).

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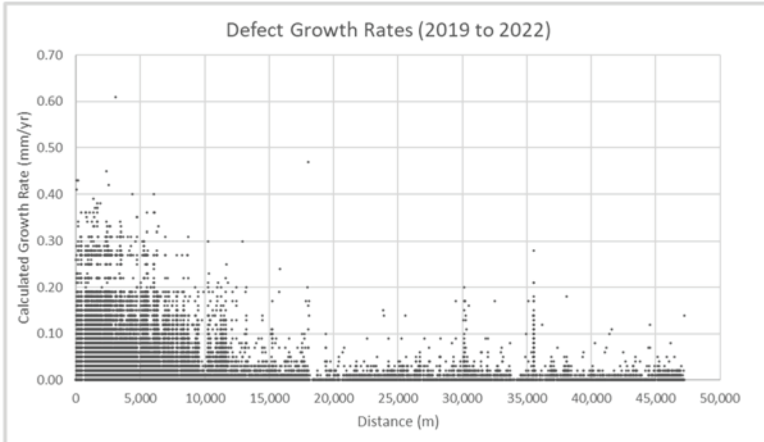

Figure 4: Distribution of Observed Growth Rates Along Pipeline Length (2019 to 2022)

The new RCG3D approach considers the past observed growth behaviour, and it also allows for different future growth behaviour via the probabilistic selection of growth rates from a localised distribution. This means that a specific corrosion defect that previously did not show any growth could be predicted to start growing if there was observed growth from other nearby corrosion sites. The probabilistic treatment of the corrosion growth is one of the advantages of this new approach over other deterministic methods.

Comparison vs Other Commonly Used Approaches

Fixed growth rates are a commonly used approach for determining the response times of clusters to exceed FPR and depth criteria. They can be derived from the full population of defects, from statistically representative samples or be segment based and can represent the maximum, average or an upper (90^{th} or 95^{th}) percentile growth rates. For the purposes of this comparison, we have selected the following three fixed rates; i) average rate 0.04mm/yr (2 mpy), ii) 95^{th} percentile rate 0.14mm/yr (5.5 mpy) and iii) the maximum rate 0.61 mm/yr (24 mpy) and a growth period of 7 years from 2022 (7 years being the ILI interval used for many pipelines).

Approach	RCG3D Scenarios		Fixed Growth Rate Scenarios		
Response Criteria After 7 years	50^{th} percentile "expected case"	95^{th} percentile "worse case"	Average rate (0.04mm/yr)	95^{th} percentile rate 0.14mm/yr	Max rate 0.61mm/yr
FPR <1.25	4	9	0	20	3617
Peak Depth >80%wt	0	1	0	0	41
Total	4	9	0	20	3621

Table 2: Number of Clusters Exceeding the Allowable FPR (<1.25) and/or Peak Depth (>80%wt) Criteria Within 7 years of the 2022 ILI Run

The results in Table 2 above illustrate that the fixed rate response times are wildly different ranging from zero clusters (average growth rate) to 3621 clusters (for the maximum growth rate) requiring a response within the 7-year period. In comparison, the two RCG3D growth rate scenarios produce reasonably close results highlighting the robustness of this new approach. Furthermore, there is overlap in the results from two RCG3D growth rate scenarios, i.e., the 4 clusters identified in the 50^{th} percentile case are also contained in the 95^{th} percentile case. Whereas only 1 of the 9 clusters

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(from the RCG3D 95th percentile case) appear in the 20 clusters in the 95th percentile fixed rate approach suggesting that 8 of the 9 clusters were assigned higher growth rates (from the local rate distribution) than the 95th percentile fixed rate of 0.14 mm/yr. This draws attention to the potential for under conservatism in assuming even a 95th percentile fixed growth rate (which would normally appear to be a reasonable choice). However, if the maximum observed rate (0.61mm/yr) is used as the fixed rate, this results in more than 3,600 clusters requiring a response within 7 years showing the potential for considerable over conservatism.

These results highlight that using fixed growth rates to predict cluster response times is not a credible approach due to the highly variable and very localised nature of corrosion initiation and growth. Using corrosion rates drawn from locally derived growth rate distributions and a probabilistic approach to predict the cluster response time provides notably more stable and realistic results.

Validation of the New RCG3D Approach

Over time we have gathered a lot of historical ILI data and have many lines with 3 or more sets of ILI data. This data has been used as part of the development, testing and validation of the new RCD3D approach. By applying the new RCG3D approach to lines which have 3 or more ILI datasets, we can use it to predict the cluster severity at the time of the 3rd or later ILI's and compare these predictions vs the actual "truth" data to determine whether the correct "outcome" is achieved (i.e., the correct prediction of the repair need). It is the ability to predict the correct outcome that is the success measure of the RCG3D approach.

For example, here is a pipeline where we have three ILI datasets from 2017, 2020 and 2023. The RCG3D approach was applied to the 2020 dataset using the corrosion growth rates observed between the previous ILI's in 2017 and 2020. The cluster severity was predicted forward by 3 years from the 2020 ILI to 2023 then compared against the actual cluster severity evaluated from the 2023 ILI run. Figures 5a. and b. show the cluster severity results (actual 2023 FPR values vs the predicted 2023 FPR values) using two growth predictions representing i) the 95th percentile "worst case" scenario and ii) the 50th percentile "expected case" scenarios.

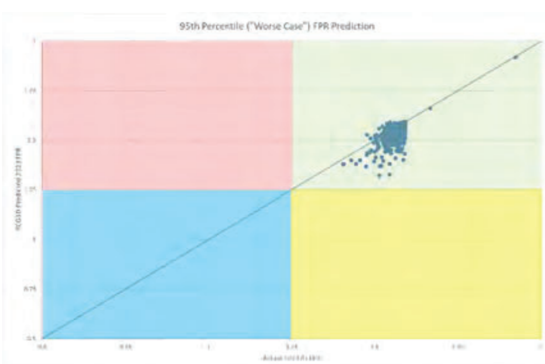

Figure 5a. Actual 2023 FPR vs Predicted 2023 FPR
95th Percentile Scenario

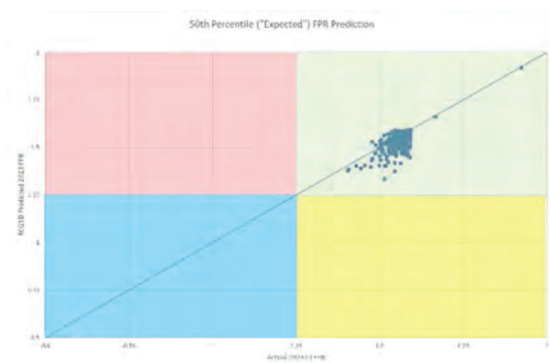

Figure 5b. Actual 2023 FPR vs Predicted 2023 FPR
50th Percentile Scenario

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The coloured areas in the above charts represent the following outcomes…

Red – Incorrect prediction (safety outliers)	Green – Correct prediction (no repair required)
Blue – Correct prediction (repair required)	Yellow – Incorrect prediction (resource outliers)

Whilst we would not expect an exact one to one match of the actual vs predicted FPR values, the predictions are reasonably close, and all are in the same quadrant in Figures 5a and 5b. This means the actual outcome of "no repair required" is correctly predicted by both RCG3D scenarios. As expected, the 95th percentile ("worse case") scenario is more conservative and shows a slightly larger spread of FPR values than the 50th percentile scenario. When predictions are made over longer time intervals the differences between the 50th and 95th percentile scenarios are more apparent.

The above results are typical of what we have seen across the other lines used for validation purposes, i.e., the "outcome" is overall correctly predicted with relatively few exceptions which mostly occur in the "yellow" area (resource outliers) rather than in the "red" zone (safety outliers).

Concluding Remarks

The determination of corrosion growth rates and their application in the prediction of future severity is a critical part of pipeline integrity management. The consequences associated with both underestimating and overestimating growth rates can be significant in terms of both safety and resource performance.

There are many ways that corrosion growth rates can be used in future integrity predictions with most approaches applying corrosion growth in the depth dimension only taking no account of surface area growth and potential interactions between adjacent corrosion areas over time. Areas of corrosion which are reported by ILI data analysis as "clusters" will change over time in all three dimensions (depth, length, and width dimensions) as the existing sites grow and new corrosion sites occur in and around/adjacent to the edges of existing areas. Two or more corrosion sites that are not touching but are close enough to interact (i.e., have a lower burst when treated as one feature vs treated as individual features) should be considered as the same area for the purposes of pipeline integrity calculations. This is handled by the ILI analysis clustering rules applied when reporting areas of corrosion, i.e., the clusters. However, when predicting future integrity of a pipeline it is the existing cluster surface dimensions (at the time of the last ILI run) that are used with typically only the depth dimension being increased by the observed corrosion growth rate.

A new approach has been developed that predicts how an area (cluster) of corrosion can grow over time allowing it to combine with other surrounding corrosion defects and with newly developing corrosion. This new approach is called Runcom Cluster Growth 3D (RCG3D) and the main differences between RCG3D, and the more established (depth growth only) approaches are:

- It does not use fixed individual defect growth rates or pipe spool growth rates, but instead uses a probabilistic simulation model to select rates from local distributions.
- The growth rate distribution is derived from a group of corrosion defects expected to be under the same or very similar corrosive environment.
- The probabilistic model is used to select individual box growth rates corresponding to 95th percentile ("worse case") and 50th percentile ("expected") scenarios.

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- The assessment accounts for growth in all three dimensions of the individual defects (depth, length, and width) and models the potential for future interaction between nearby areas of corrosion via a machine learning neural net model to predict plausible sites and patterns of new defect initiation.

The new RCD3D approach has been validated by comparing the cluster severity predictions (in terms of the "outcome") against the "truth" data from pipelines which have 3 or more ILI datasets. RCD3D is applied to the 2nd ILI data and used to predict the "outcome" at the time of the 3rd (or later) ILI run. The results obtained were found to be realistically conservative, i.e., the approach maintains an acceptable level of safety whilst minimising the numbers of resource outliers (unnecessary repairs).

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