ADVANCES IN MAGNETIC FLUX LEAKAGE SIGNAL MATCHING AND CORROSION GROWTH RATE SELECTION

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ABSTRACT
Safe operation of pipelines carrying corrosive products or in a corrosive environment requires (i) an understanding of the corrosion threats, (ii) the ability to estimate corrosion growth rates (CGR) of features; and (iii) the ability to apply these rates to plan future inspections, repairs and replacements. Reducing uncertainties in corrosion behaviour will therefore result in safer, more cost efficient operation.

This paper provides:

- An overview of methods used in the industry for estimating CGRs (e.g. coupons, corrosion modelling, box matching and signal matching).
- A discussion of the challenges involved with Magnetic Flux Leakage (MFL) signal matching; and how advances in pattern recognition and data pre-processing, now allow full automated matching of signal data from repeat inspections.
- A comparison of different ways of using CGRs (e.g. feature specific rates, maxima, upper bounds, segmented rates) and a methodology for selecting the best method, to ensure safety while minimising repair and re-inspection requirements.
- Case studies demonstrating the efficacy of using signal matching and a tailored CGR application method.

1 INTRODUCTION

Predictions of future corrosion activity support pipeline operators with critical Integrity Management (IM) decisions, such as generating repair plans, scheduling corrosion mitigation activities, defining re-inspection intervals and estimating remnant life [1]. These predictions are made through the estimation and application of corrosion growth rates (CGR) for the features present in a pipeline.

CGR is defined as the rate of increase of corrosion depth with time. Since corrosion is governed by a complex set of electrochemical, kinetic and metallurgical processes however, this rate is rarely constant. Growth of a feature can initiate, arrest, accelerate or decelerate over time, due to changes in the local environment. Uncertainty associated with CGR measurements is therefore high and significant engineering expertise is required to make informed predictions [2].

This uncertainty highlights the need for inspection vendors and integrity engineers to continually advance technology, improve knowledge and build experience in corrosion growth prediction. This paper discusses recent innovations in this field, and provides guidance on how to best estimate and use CGRs for pipeline integrity management.

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2 BACKGROUND

Corrosion growth assessment involves two key stages, namely the estimation and application of CGRs. Much industry effort has focused on improving the efficacy of these two stages [3],[4],[5].

2.1 Estimation of CGRs

There are many options for estimating CGRs to use in pipeline integrity management; these include methods based on:

- Corrosion modelling
- Coupons and probes
- Industry guidance
- Repeat ILI 'box' matching
- Repeat ILI signal matching

An overview of these approaches is given below.

2.1.1 Corrosion Modelling

Theoretical modelling of CGRs in the oil and gas industry is primarily focused on the prediction of carbon dioxide (CO_2) corrosion of carbon steel. For pipelines, these models will typically be applicable to internal corrosion caused by a corrosive product.

Oil and gas companies and research institutions have developed a number of prediction models for CO_2 corrosion; some are described in the open literature, whereas others are proprietary. The prediction models can be classified into three broad categories, based on how firmly they are grounded in theory [16]:

- **Mechanistic models** – These models describe the mechanisms of fundamental reactions and have a strong theoretical background. Examples include Hydrocor (Shell), KSC Model (Institute for Energy Technology (IFE)) and Multicorp (Ohio University)
- **Semi-empirical models** – These models are only partly based on theoretical hypotheses. They are for practical purposes extended to areas where insufficient theoretical knowledge is available, in a way that additional phenomena are described with empirical functions. An example of a semi-empirical model used for pipelines is the De Waard Model [6].
- **Empirical models** – Empirical models have very little or no theoretical background and are typically based on direct observation, measurements from experimentation, and extensive data records. Examples of empirical models include the NORSOK M-506 model (Statoil, Norsk Hydro and Saga Petroleum) [7] and Electronic Corrosion Engineer (ECE®) (Intetech) [8].

CO_2 corrosion model outputs are highly variable and also highly sensitive to parameters such as oil wetting, temperature, pH and protective film effects. It is therefore unsurprising that validation of models against field data has met with varying levels of success. Given that certain models are more successful under specific conditions [17], operators and integrity engineers require very specific knowledge of the corrosion cause/mechanism and operational conditions in order to make informed predictions.

2.1.2 Coupons and Probes

Corrosion monitoring devices such as:

- Weight Loss Coupons (WLC),
- Linear Polarisation Resistance (LPR) probes, and
- Electrical Resistance (ER) probes

have been extensively used in the industry to provide a physical measurement of CGRs. A survey [9] suggested that WLCs have been the most widely used monitoring instruments in the field. Experience of field monitoring with coupons and probes has been somewhat variable, and has generally been reported as "not reliable", or at least not as accurate as laboratory monitoring.

Some of the main reasons for this are:

- The operating conditions in the field can vary widely and these could have a significant effect on which corrosion mechanism(s) is realised, and whether a corrosion mechanism will actively continue in a steady process, be accelerated or arrested. Without a clear understanding of operational and mitigation regime fluctuations and their influence on the realisation of corrosion mechanism(s), implementation of corrosion measurement(s) reported by WLC for pipeline integrity management and remaining life assessments becomes meaningless.
- The type and location of the monitoring devices have often not been selected in relation to corrosion risk expectations. In many cases, the success of a good monitoring system relies on preliminary corrosion risk assessment activities, to determine the nature of potential corrosion mechanisms (e.g. CO_2 corrosion vs. Microbiologically Induced Corrosion), morphologies (e.g. general vs. localised), and the locations of the most susceptible locations (corrosion hot spots) (e.g. top-of-line vs. bottom-of-line). Anticipation in terms of corrosion mechanisms, morphologies and hot spots is critical to drive the design of a successful monitoring strategy, including the selection of monitoring devices and their location in the system. Even a wisely and judiciously developed corrosion monitoring strategy may become obsolete (i.e. not representative of reality) over time, due to the dynamic nature of operations and variations in corrosion mechanisms and hot spots.
- Lack of awareness of instrument technique limits, for example ER probes may be used in any liquids, whilst the LPR probe may only be used in conductive electrolytes. Both can be used as on-line devices and can deliver instantaneous CGRs; however, they only provide indication on general corrosion rates. Weight loss coupons can provide an indication of general and localised rates, but require both removal from infrastructure and extended exposure time, before providing meaningful information.

As an example [10], Figure 1 compares the CGRs of probes placed in an oil and gas production pipeline and that of the pipeline itself. The CGRs of the coupons clearly vary in relation to their location in the pipeline:

- The coupons at the bottom suffered the highest CGRs, due to exposure to the aqueous phase.
- The middle coupons showed moderate CGRs, due to exposure to both aqueous and oil phases.
- The coupons at the top presented the lowest CGRs, due to partial exposure to gaseous phase.

In this example, the coupons suffered higher corrosion growth than that of the pipeline, since the flow shear stress on the coupons was higher than that on the internal pipe wall.

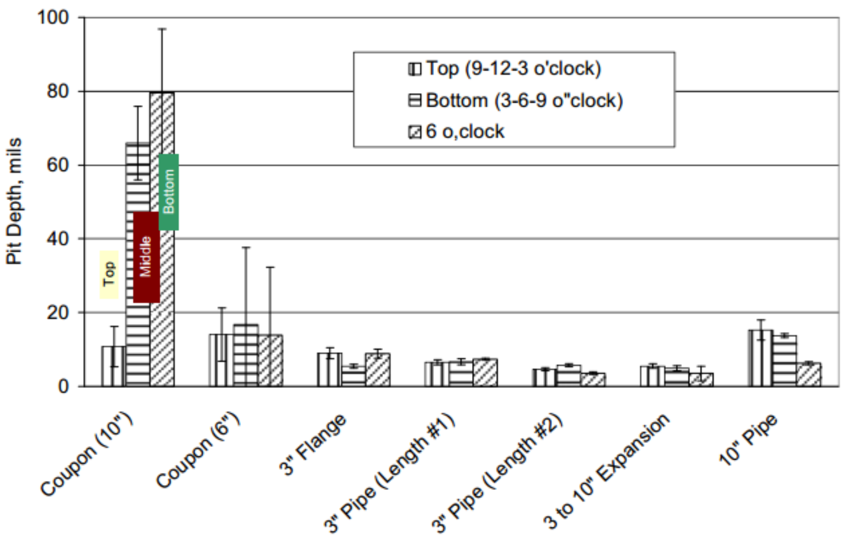

Figure 1: Comparison of pit depths from coupons with those actually measured in pipeline section [10]

The example above focuses on CGRs monitored in an internal pipe environment. Coupons have also been used to monitor the efficiency of external cathodic protection (CP) systems on pipelines and overcome the error measurement associated with IR drops. The ability of a coupon to monitor the effectiveness of a CP system, was evaluated by the Pipeline Research Council International Inc. (PRCI). Tests compared the coupon instant-disconnect potential, with the instant-off potential of the pipeline. Although there was a strong correlation between the coupon and pipe instant off-potential, a significant scatter in data was reported (see Figure 2). It was highlighted that to provide a good measurement of the CP effectiveness, coupons need to be located in a region near actual pipe coating defects; and the coupon coating holiday "shall have a surface equal or less than that of coating defects actually existing on pipe surface".

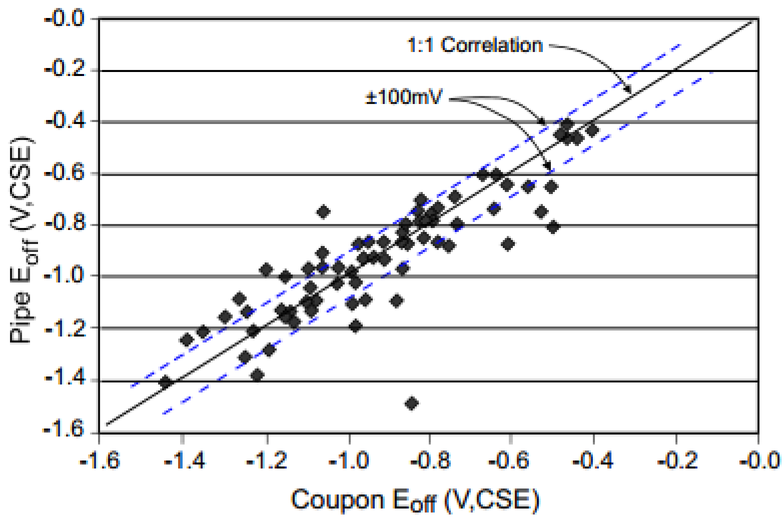

Figure 2: Pipe vs. coupon off-potential [12]

2.1.3 Industry Guidance

In the case of internal corrosion, CGRs are largely dependent on the nature of the corrosion mechanisms. This is largely driven by the type and chemistry of fluids and operational parameters; e.g. pressure, temperature, flow rate.

In the case of external corrosion of buried pipelines exposed to soil environments, CGRs have been defined based on the soil corrosivity, which can be derived by consideration of:

- Soil type and extent of contamination / pollution
- Resistivity
- Moisture content
- pH
- Presence of chlorides, sulphates, sulphides
- Microbial load
- External electrical interferences
- etc.

NACE has produced a recommended practice for External Corrosion Direct Assessment (ECDA) [11], which includes guidance on CGR estimation that includes the methods discussed in this paper. This states however, that when possible, external CGRs should be determined by directly comparing measured wall thickness changes over a known time interval (from in-field or in-line inspections).

When other data are not available, a default pitting rate of 0.4 mm/year is given for determining reinspection intervals. This is based on bare steel without CP and can be reduced by a maximum of 24%, provided the CP system can be shown to meet specific performance requirements.

Table 1 and Table 2 show a wider range of typical industry external CGRs, based on type and corrosivity of soils.

Table 1: Example Of External Corrosion Rates Based On Soil Corrosivity (NACE paper No 02075 [13])

Resistivity, ohm.cm		Soil type	Water types	Corrosivity	mm/yr
	<100		Seawater, brines	extremely	1.0
100	<1,000	salt marshes, salty peat, swamps	Sea-bed	highly	0.5
1,000	<5,000	salt loams, wet loams, clays, peat	Brackish water	moderately	0.2
5,000	<20,000	compact loams, clays,	Fresh water, Riverbed	slightly	0.1
20,000	<50,000	sandy loams, gravel		slightly	0.05
≥50,000		lime stone, dry sand, rock debris,		not expected	(≤)0.05

Table 2: Example Of External Corrosion Rates Based On Soil Corrosivity (DIN 50929 Part 3 [14])

Soil corrosivity*	Risk Of General Corrosion	Range Of General Corrosion Rate mm/year	Risk Of Localised Corrosion (pitting)	Range Of Pitting Rate mm/year
Virtually not corrosive	Very low	0.0025-0.01	Very low	0.015-0.06
Slightly corrosive	Very low	0.005-0.02	Low	0.03-0.12
Corrosive	Low	0.01-0.04	Medium	0.1-0.4
Highly corrosive	Medium	0.03-0.12	High	0.2-0.8

**Soil corrosivity assessment methodology is defined in DIN 50929*

DNV RP F101 [15] now includes a section regarding estimation and application of CGRs. A lot of the caveats and limitations mentioned within this paper are discussed, particularly the need for historical and future operation to be considered in the assessment, with input from a corrosion specialist. Four methods of estimating remaining life are given, starting with a deterministic approach that uses a conservative upper bound estimate of CGR for each user defined segment (conservative segmentation is recommended based on engineering judgement). The upper 95th percentile rate is suggested as a suitable CGR. This is a parametric percentile based on a normal distribution, though our analysis process (see Section 2.2.2) uses a non-parametric value. These two approaches will be similar when using a box matching distribution but not when using signal matching, as a true CGR distribution is not expected to be normal.

Semi and fully probabilistic approaches are also discussed in RP F101, together with a method specifically related to detailed Ultrasonic Wall Thickness measurement ILI data.

2.1.4 Repeat ILI: Feature (“Box”) Matching

In a box matching process, repeat ILI runs are aligned to the same reference log distances, typically using girth welds. Features are then “matched” between the two inspections and a depth difference calculated, based on the reported depths of each corrosion feature in the successive inspections. A CGR is calculated assuming linear growth over the inspection interval. “Unmatched” features (i.e. those without a corresponding feature reported previously) may represent new corrosion growth; however these are often associated with features that were not reported previously due to detection capabilities and/or depth reporting thresholds (often features below 10% of wall thickness are not reported). The accuracy of the CGRs determined by feature matching is heavily influenced by the accuracy of the matching algorithm and the depth sizing accuracy of the two inspections.

2.1.5 Repeat ILI: Signal Matching

In signal matching, CGRs are determined by directly comparing the signal data from the two inspections, using the change in signal amplitude and shape following normalisation of the magnetic response. The matched signals can be used to calculate a depth change using the same sizing model, which corresponds to in-service growth. This type of assessment significantly improves the accuracy of the calculated historic CGRs. The approach of signal matching is particularly useful for calculating CGRs for apparently “new” reported features, which may have previously been present in the signal data but sized below the reporting threshold. As the analysis uses normalised full data sets from both inspections, all indications are available for matching. A fully signal based quantitative assessment such as this is only possible for same-vendor, same-technology comparisons. It should be noted however, that feature or “box” matching results can be improved by completing qualitative manual signal comparisons for selected features. This type of manual visual assessment is not restricted to same-vendor comparisons.

2.2 Application of CGRs

Once CGRs have been estimated, a decision must be made as to how these CGRs are selected (note that different credible rates can be estimated for the same pipeline and even the same sections) and applied to a pipeline, in order to predict future severity of reported corrosion features. When this is being done for investigation and repair scheduling, it is important to make conservative predictions. If these are over conservative however, significant and unnecessary costs can be incurred.

2.2.1 Prediction Methods in Deterministic Assessments

In the case of feature matching following repeat ILI runs (either by box matching or signal matching), a CGR is obtained for each reported feature. A common misconception is that the most accurate prediction will be achieved when each feature is grown at its own historical rate. In fact, this method simply magnifies the uncertainty associated with individual CGR measurements and yields scattered, inaccurate predictions. The method also assumes that each corrosion feature behaves as if in isolation, when in reality the same corrosion cause (and activity) may be present over a much larger area [3]. Case Study 2 includes a clear illustration of this effect, based on analysis of actual repeat ILI data.

A more pragmatic approach is to select a single “representative” CGR from the population and apply this to all reported corrosion features. The most conservative example of this method, is the use of the population maximum. This level of conservativism is recommended in cases where the future corrosion behaviour is particularly uncertain, for example due to significant changes in operation or environment (aggressive cleaning, increase in water cut, degradation in CP performance, flooding etc.). For cases of stable operation however, the maximum CGR typically results in a high number of unnecessary repair predictions. More realistic results can often be obtained using a less conservative “upper bound” CGR such as the 95th percentile (either parametrically as recommended in DNV RP F101, or non-parametrically) or the mean plus one standard deviation.

For pipelines with significant changes in corrosion activity along their route, it is often beneficial to use a segmentation method, whereby representative CGRs are applied to different sections of the pipeline. The segmentation may separate out the pipeline into individual pipe joints or into larger segments, based for example on changes in corrosion cause/mechanism, measured CGRs or other monitoring/survey data that indicate a change in corrosion threat.

2.2.2 Optimal Selection of Prediction Method

A methodology for the selection of an optimal prediction method has been developed, based on a pipeline’s measured corrosion activity and inspection history.

The method (described in full in [3]) can be applied to pipelines with 3 or more ILI datasets. CGRs are calculated by matching features between the first 2 ILI runs. The CGRs are then applied to the results of the 2nd ILI and a prediction is made of the state of the pipeline at the time of the 3rd ILI. This can then be compared to the actual inspection results on a unity plot (showing measured depth vs. predicted depth). The success of a method is determined heuristically by its ability to:

1. prevent underestimation of corrosion depths, which can lead to a compromise of safety
2. limit overestimation of corrosion depths, which can lead to unnecessary repairs

Based on these criteria, each point on the unity plot is assigned its own prediction category (Table 3). These categories are based upon (i) whether or not the prediction is conservative (i.e. located below or above the unity diagonal), and (ii) whether or not the correct repair decision would be made based upon the prediction. “Repair decisions” are determined by calculating the critical depth of each reported feature. This is taken as the minimum critical depth according to the Modified ASME B31G and Kastner assessment methods [18],[19], for an assessment stress equivalent to 100% of the Specified Minimum Yield Strength (SMYS) of the pipeline. Clustering and depth sizing tolerances are not considered for these calculations.

Table 3: Prediction categories for unity plots

	Conservative Prediction	Non-Conservative Prediction
Correct Repair Decision	Depth overestimated, but correct decision made (i.e. repaired only if necessary)	Depth underestimated, but correct decision made (i.e. repaired only if necessary)
Incorrect Repair Decision	Depth overestimated, and incorrect decision made (i.e. repaired unnecessarily)	Depth underestimated, and incorrect decision made (i.e. not repaired when necessary)

If the prediction and measurement both agree on the criticality (or sub-criticality) of the feature at the time of the 3rd ILI, then the repair decision is considered to be correct, and *vice versa*.

Based on the categories in Table 3, a successful method is one which:

- maximises the number of conservative predictions leading to correct decisions (green points)
- minimises the number of unnecessary repairs (yellow points)
- limits the number of non-conservative predictions (blue points), and
- avoids potential (code) failures (red points).

The level of success can be measured using a heuristic scoring methodology as outlined in [3], or observed qualitatively as in the following case studies.

3 CASE STUDIES

This paper discusses 2 separate options for improving corrosion predictions in pipelines inspected multiple times by MFL ILI technology. These are:

1. estimation of CGRs using an MFL signal matching process
2. identification of a CGR application strategy which is tailored to the corrosion behaviour of the pipeline under consideration

The following case studies demonstrate the efficacy of using these options, when conducting deterministic future integrity studies.

3.1 Case Study 1

The first case study is for an onshore pipeline inspected with ROSEN axial MFL technology in 2004, 2007 and 2013. The 2013 inspection reported 781 external corrosion features, and a review of historical pipeline data suggested that the corrosion had been caused by general degradation of the external coating.

CGR prediction options were analysed using the unity plot methodology outlined in Section 2.2. CGRs were estimated via box matching between the 2004 and 2007 ILI datasets, and used to predict the state of the pipeline at the time of the 2013 inspection.

Firstly, predictions were made based on a conservative maximum CGR of 0.72 mm/year (Figure 3). All predicted depths resulting from this method were conservative (plotted below the diagonal) and 680 features were predicted to require repair by the time of the 3rd ILI. Based on the actual measurements from the 3rd ILI, however, only 2 defects were considered to require repair. Consequently, the application of the maximum CGR resulted in the prediction of 678 unnecessary repairs (represented by yellow points).

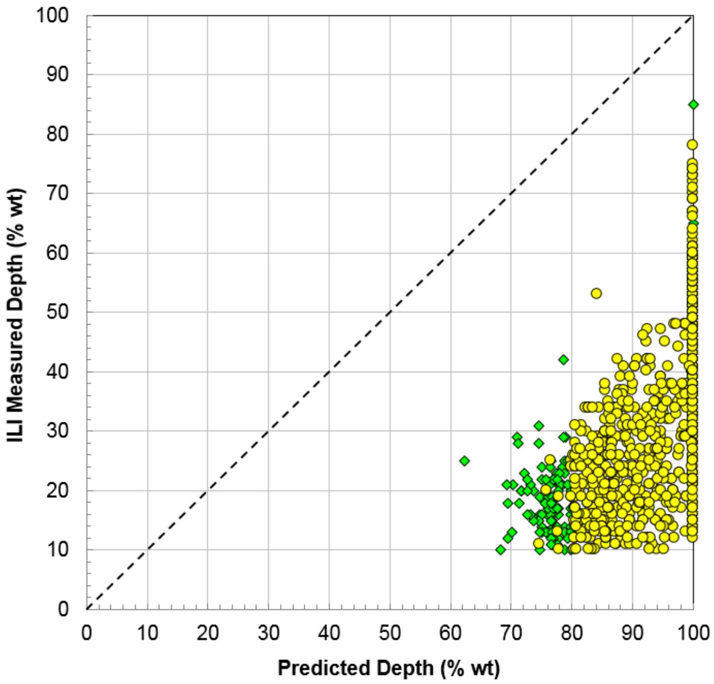

Figure 3: Unity plot for Case Study 1, maximum CGR

As an alternative, an upper bound CGR of 0.24 mm/year was applied (Figure 4), based on the non-parametric 95th percentile. The result is still conservative; only 2 feature depths were underestimated and the maximum underestimate was only 11% of wall thickness. However, there is a marked (> 90%) reduction in the number of predicted repairs, from 680 down to 56. Furthermore, the majority of the 54 repairs which are considered "unnecessary" were measured with depths in excess of 50% of wall thickness and as such would be likely to become critical with only a small amount of additional growth. This is in contrast to the case in Figure 3, where even insignificantly shallow features were predicted to require repair.

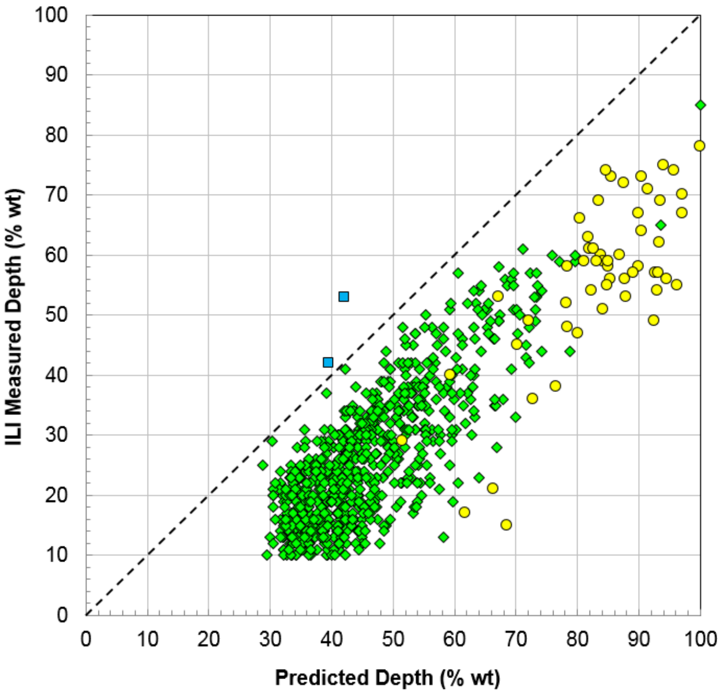

Figure 4: Unity plot for Case Study 1, upper bound CGR (non-parametric 95th percentile)

Other case studies completed by the authors have provided evidence that an upper bound statistic from box matching provides a conservative, yet realistic estimate of the CGR in pipelines where (i) the corrosion activity is not expected to vary significantly along the pipeline route, and (ii) where operation is stable over time. Both conditions were met in Case Study 1. The signal comparison in Figure 5 shows a typical external corrosion feature from the pipeline exhibiting steady, predictable corrosion growth.

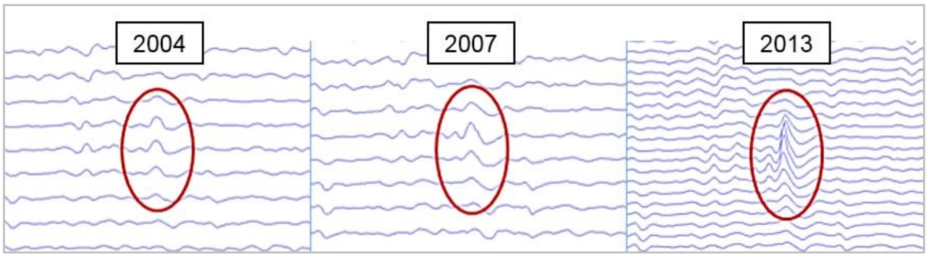

Figure 5: Signal comparison showing evidence of steady external corrosion growth in Case Study 1

In contrast to the above, Case Study 2 demonstrates the level of care required in cases of unstable, unpredictable operation.

3.2 Case Study 2

The second case study relates to an onshore pipeline inspected in 2006, 2011 and 2015 using ROSEN axial MFL technology. A 40 km section of the pipeline was analysed, which contained 873 external corrosion features. The pipeline history suggested that much of the corrosion had been caused by sustained cathodic overprotection between the 2011 and 2015 inspections, which had caused damage to the coating and subsequent shielding from the CP system (different from the conditions between 2006 and 2011).

CGRs were first estimated using box matching (between the 2006 and 2011 inspections) and used to predict the state of the pipeline at the time of the 2015 inspection. Using the maximum CGR of 1.64 mm/year, the unity plot in Figure 6 was obtained.

All predictions were conservative and 19 defects were predicted to require repair. Based on the 2015 inspection results, however, no features were considered to require repair. All 19 of these predicted repairs were therefore considered unnecessary (yellow points).

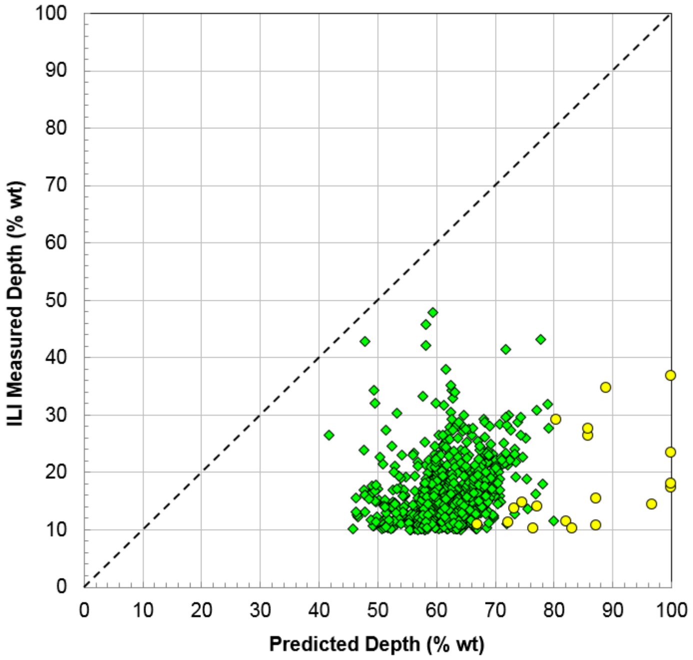

Figure 6: Unity plot for Case Study 2, maximum CGR obtained via box matching

The CGR distribution was re-evaluated using a signal matching approach (including pattern matching), which yielded a new maximum CGR of 0.69 mm/year. The updated unity plot is displayed in Figure 7, which shows a considerable improvement in prediction accuracy, and a reduction in the number of unnecessary repairs from 19 to 4. This is at the expense of a number of under-predictions, although the greatest of these (17% wall thickness) is considered tolerable.

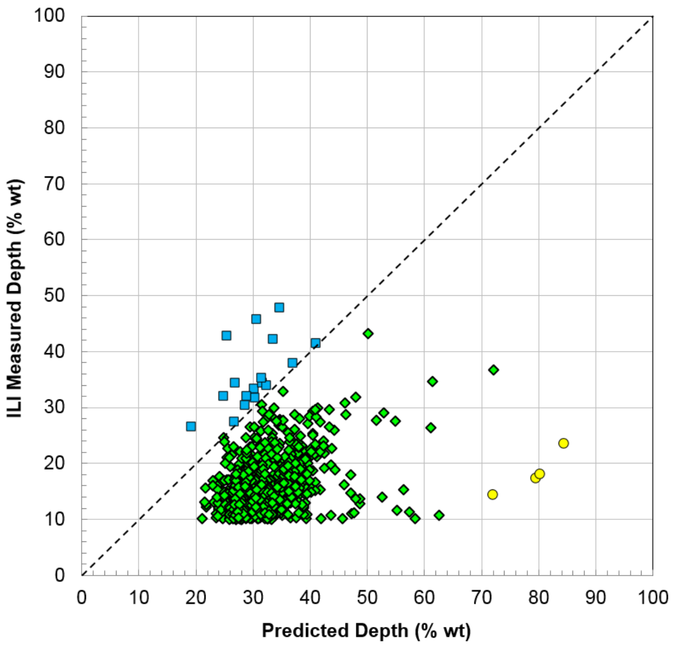

Figure 7: Unity plot for Case Study 2, maximum CGR obtained via signal matching

This clear improvement can be ascribed to a reduction in the uncertainty associated with the individual CGR measurements. Generally speaking, the maximum calculated CGR in a pipeline will be associated with one of the deepest reported features (either unmatched, or matched to a shallow feature in the previous inspection). In this particular case study, the maximum CGR (from box matching) of 1.64 mm/year was obtained for the second deepest reported feature in 2011 (64% wall thickness).

It can be shown that the deepest reported features are statistically more likely to have the largest (positive) errors, and will consequently lead to the greatest overestimates in CGR when using a box matching approach [20][1]. However, by using signal matching, it becomes more likely that the population maximum represents true peak activity. The new estimated maximum of 0.69 mm/year is therefore considered to be a better representation of the true population maximum.

Further insight can be obtained by observing the full CGR distributions. When considering these distributions, a distinction must be made between a measured distribution and a true distribution. Any true CGR distribution must be non-negative and (except in the case of very high CGRs) positively skewed [21]. In contrast, a measured CGR distribution is unconstrained, as measurement errors can often result in negative CGR values. This is particularly true of CGRs derived from box matching, as evidenced by Figure 8, which shows frequency histograms of the CGRs obtained from box matching and from signal matching.

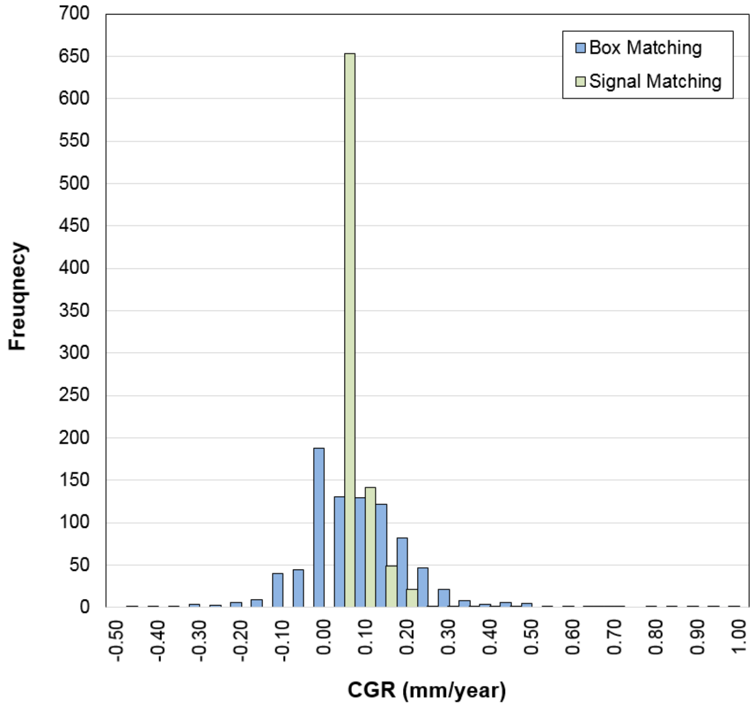

Figure 8: Frequency histogram for Case Study 2 showing CGRs for box matching and signal matching

The histogram displays clearly that the signal matching distribution has characteristics closer to that expected of a true CGR distribution. Due to a reduction in measurement error, the signal matching CGR distribution is non-negative, positively skewed and lower in variance.

Although the signal matching distribution gives a better representation of corrosion activity between 2006 and 2011, the unstable operation means that this historical distribution does not appropriately model the general increase in external corrosion activity thereafter. As such, attempting to use the same approach as in Case Study 1 leads to under-conservative results.

Figure 9 shows a third unity plot obtained by using non-parametric 95th percentile CGRs, after segmenting the pipeline into 3 sections. The corresponding CGRs for the 3 sections were all below 0.22 mm/year.

[1] The CGR associated with this feature obtained from box matching (i.e. the maximum of 1.64 mm/year), was reduced to 0.40 mm/year when a signal matching process was adopted.

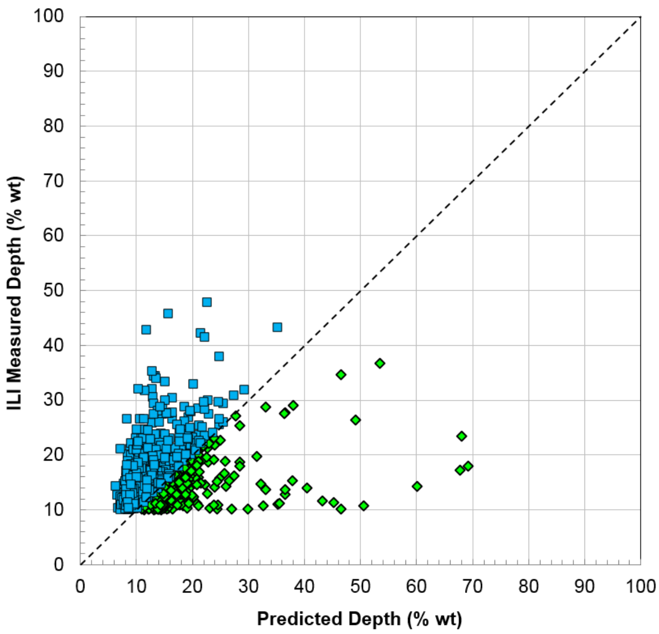

Figure 9: Unity plot for Case Study 2, segmented upper bound CGR (non-parametric 95th percentiles) obtained via signal matching

The result is that over half of all reported predicted depths are non-conservative, with a maximum under-prediction exceeding 30% wall thickness. This level of under-prediction is considered unacceptable.

The signal comparison in Figure 10 shows the evolution of a typical external corrosion feature, and demonstrates clearly why the upper bound method fails in this case. Although corrosion growth between 2006 and 2011 is minimal and may perhaps be well modelled by a 95th percentile CGR (i.e. ~0.22 mm/year), growth between 2011 and 2015 was more rapid and would be better modelled by the maximum CGR (i.e. ~0.69 mm/year).

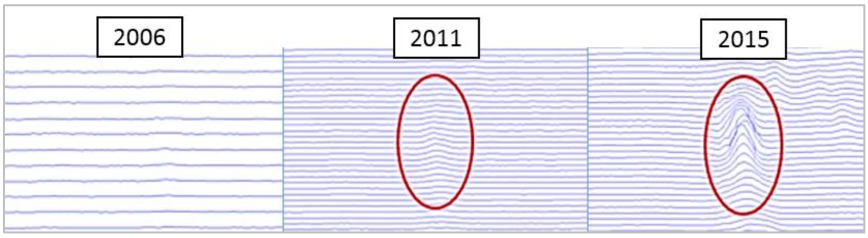

Figure 10: Signal comparison showing evidence of unsteady (accelerating) external corrosion growth rates in Case Study 2

In addition to the above, it is interesting to look at the how the changes in feature depths vary between the first and second inspection intervals. Figure 11 shows the CGR calculation results of both box and signal matching for each feature, when plotted against each other for the two intervals.

A first observation from the plot is that the maximum CGR calculated via box matching has decreased between the first and second intervals, while the equivalent maximum from signal matching has increased. Given the known fact that corrosion activity increased over the second interval, it is clear that the signal matching CGRs are a better representation of true growth behaviour.

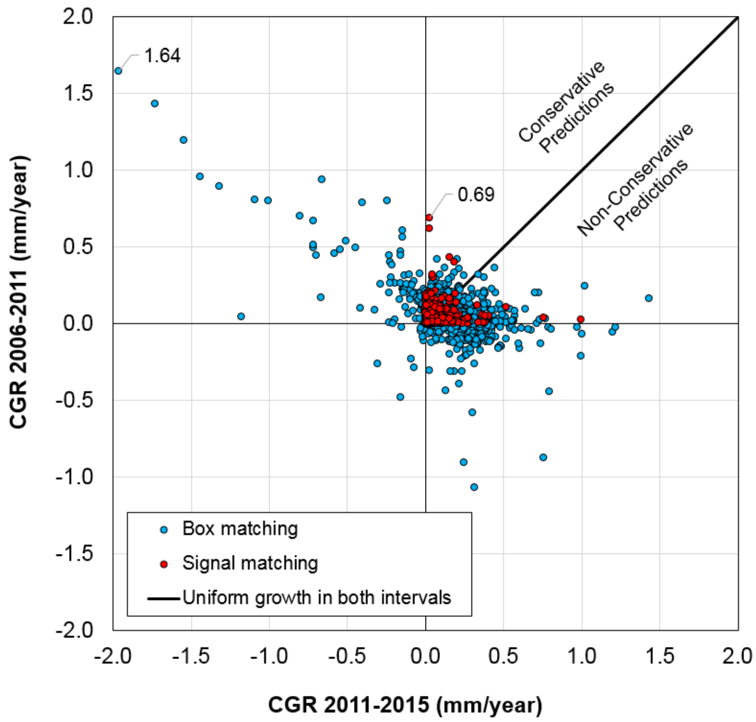

Figure 11: CGRs for individual corrosion features, 2006-2011 interval vs. 2011-2015 interval

A second point to note is the lack of correlation between CGRs for individual features over the two intervals, for both comparison methods. If growth behaviour for each feature had been uniform over the two intervals, the points would generally be centred around the unity line. This is emphatically not the case however, and there are some extreme examples of differing behaviour over the two intervals.

The highest growth feature in the signal matching results for the second interval had a calculated CGR of 1.00 mm/year for example, but this feature had shown only a calculated rate of 0.02 mm/year over the first interval. This result was confirmed by manual signal comparison. Application of the first interval rate to this feature would have resulted in a significant growth underestimate, a strong argument against using individual rates as a prediction tool. If this method were used for making future integrity predictions, all points located above the diagonal would lead to conservative predictions, while all points located below the diagonal would lead to non-conservative predictions.

In an effort to avoid this fundamental problem with individually calculated CGRs, a common approach is to use the maximum CGR in each pipe spool (joint) as a representative rate for all features therein. An equivalent plot resulting from this process is shown in Figure 12.

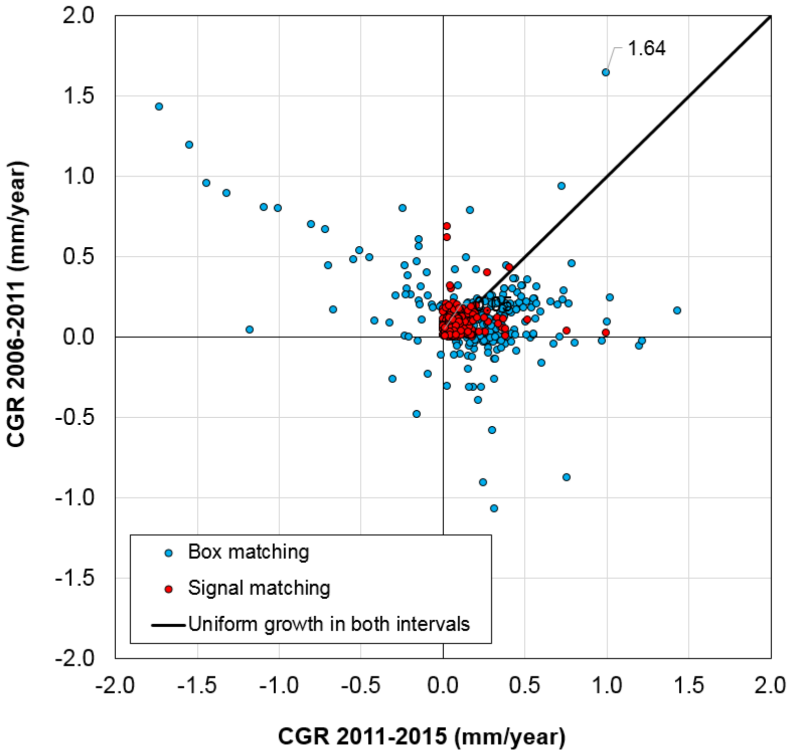

Figure 12: Maximum CGRs per pipe joint, 2006-2011 interval vs. 2011-2015 interval

Figure 12 shows that the pipe joint segmentation offers only a marginal improvement in the overall correlation, relative to the use of individual CGRs; however, predictions in localised areas may be improved somewhat. Particularly notable is the point relating to the maximum box matching CGR (over the first interval) of 1.64 mm/year. In Figure 11 (top left) it is shown that the calculated CGR for this feature drops dramatically over the second interval, implying an arrest of corrosion growth for that feature alone. Nonetheless, the location of this point in Figure 12 suggests that growth elsewhere in the pipe joint continued at 0.99 mm/year.

This demonstrates that future growth of a specific feature cannot necessarily be inferred from the historic behaviour of the feature itself. Rather, local corrosion behaviour should be predicted by analysing corrosion behaviour on a wider scale. Practically this is achieved by segmenting a pipeline into regions of perceived similar corrosion activity. Based on the poor correlation in Figure 12 and past experience however, the authors do not consider individual pipe joints to be an appropriate method of segmentation for many corrosion causes. Instead, pipelines should be split into wider segments, based on physical (less arbitrary) justifications.

A final observation for both charts, is that reducing uncertainty in the depth comparison calculation (using signal matching) helps make the rates more realistic, but does not help with the correlation. This is because the variation in rates over time is a physical phenomenon (corrosion growth behaviour is very variable), not just a statistical one.

This case study highlights the need for corrosion engineering expertise and experience, when attempting to minimise conservatism in predictions. Blind reliance on statistics can, in many cases, lead to under-conservative results.

4 SUMMARY AND CONCLUSIONS

This paper has discussed different approaches to estimation of corrosion growth rates and how to apply them in future integrity predictions, illustrated with two case studies. These demonstrate how repeat ILI data can be used to optimise the way in which future integrity calculations can be applied to a specific pipeline. They also demonstrate the need for a sound understanding of past and expected future operation. On this basis, the following conclusions are made:

- CGRs derived from repeat ILI data provide a good indication of historic CGRs.
- CGRs from box matching will be influenced by sizing accuracy, though the associated error is independent of reinspection interval, so it diminishes in terms of rate over longer intervals:
    - Optimum reinspection interval is therefore a balance, between measuring change with sufficient accuracy vs. avoiding growth of features to unacceptable dimensions.
- Signal matching, normalisation and comparison offers significant improvement over box matching and will reduce MFL sizing effects:
    - In order to ensure safety in future integrity predictions, the results of signal matching should therefore be used differently from those of feature matching approaches.
- It is possible to use historic sets of inspection data to tailor a prediction method to a particular pipeline, but:
    - It is essential that the assessment includes a thorough understanding of past and predicted future operation, linked to corrosion diagnosis by a competent corrosion engineer in order to support any attempt to reduce conservatism.
- In cases of stable operation, it may be appropriate to apply representative segment upper bound CGRs, but:
    - If there is reason to believe corrosion activity could increase (i.e. higher CGRs), use a more conservative method.
- It is not appropriate to apply feature or spool specific CGRs, as future corrosion behaviour shows a large degree of variability and is most unlikely to be uniform for specific features or spools over successive intervals. Variation in corrosion activity along a pipeline, should instead be captured using a physically justified segmentation method.

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