Enhancing External Corrosion Direct Assessment With Machine Learning

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Abstract

Operators need to keep their pipelines fit for purpose, maximize life and control costs. External corrosion is one of the main threats faced by operators, costing millions annually in identification, mitigation and repair. Although many methods exist to model the growth of corrosion features, the situation is often most complicated for "unpiggable" pipelines.

Where in-line inspection (ILI) is not possible, knowledge-based models reliant on data and assumptions for multiple variables are used. Combining the variables that are believed to contribute to corrosion is known as external corrosion direct assessment (ECDA). However, ECDA can often require multiple iterations of costly excavations to get right!

This paper discusses the use of the ROSEN Virtual-ILI (V-ILI) tool to enhance the ECDA process and demonstrates where V-ILI was used as part of the ECDA process to provide additional input data and higher confidence without the need for further excavations.

1. Introduction

The ECDA process has been utilized in many forms for the past 30 years but was only included in an internationally recognized standard in 2010 (ANSI/NACE SP502). This standard formalized the approach of ECDA into the four stages we recognize today, founded on the simple integrity management loop of Plan, Do, Check, Act:

- **Stage 1 – Plan – Preassessment:** Data collection and initial analysis to decide on the inspection methods to be used and, most importantly, whether the ECDA approach is feasible.

- **Stage 2 – Do – Indirect Inspection:** Indirect inspection of the pipeline by desktop study and aboveground surveys to identify and rank external corrosion hotspots.

- **Stage 3 – Check – Direct Examination:** Excavation at the hotspot sites to confirm or disprove the presence of corrosion.

- **Stage 4 – Act – Post Assessment:** Review of the results from the ECDA process and fitness-for-purpose/service assessment to finally generate the definition of the reassessment interval.

At the core of the standard ECDA approach is its reliance on data quantity and, most importantly, data quality, which is undoubtedly the weak link in the chain. As with any predictive modelling, "bad data in = bad information out." Hence, using the input factor carelessly can render the entire ECDA useless in the eyes of operators and regulators.

To improve the data resolution of the standard ECDA process, virtual in-line inspection (V-ILI) based on the Integrity Data Warehouse (IDW) was used to incorporate data collected over many years by ILI. V-ILI combines other relevant data, such as rainfall, soil type and coating, with information of corrosion trends across thousands of pipeline segments stored in the IDW. Through machine learning algorithms trained on this historical data, the incorporation of V-ILI has the potential to substantially reduce the uncertainty of ECDA by looking at the corrosion behavior on thousands of similar piggable pipelines. This process expands the data horizon by not only considering the local results of the pipeline in question but also how every other pipeline identified in the IDW has behaved.

2. Virtual-ILI

A pipeline (or pipe joint) has a number of parameters that describe it, including design, construction and location information; they are used as predictor variables and form the basis of the inputs for the machine learning models. Previous studies [1, 2, 3] have shown positive results using V-ILI to predict third-party damage as well as the density and maximum depth of external corrosion anomalies. In addition, generalized corrosion growth rate distributions that can be applied to pipelines with similar location and construction attributes have also been generated. Expanding on the success of these studies, the V-ILI model has been adapted to be used in support of ECDA.

V-ILI [1] is the process of using machine learning methods to learn from a global database of pipeline inspection information for the purpose of predicting the likely condition of an unseen pipeline, one that either still has to be inspected or cannot be inspected with conventional ILI tools (Figure 1).

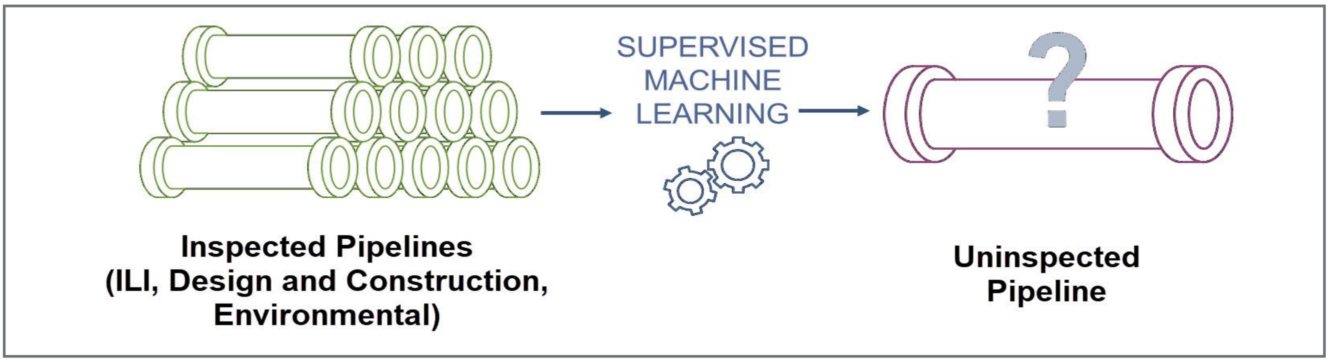

Figure 1: The fundamentals of Virtual-ILI

The final stage of ECDA (post-assessment) involves correlating the expected findings with the results of the direct examination, i.e., did we find what we expected – lots of corrosion or none at all? Although finding what you expect is a positive sign, there is still the uncertainty with regards to inspection coverage; for example, "if I had excavated 10 cm further, would I have found an 80% wall thickness defect?"

This is where V-ILI aims to provide confidence, especially in supporting the expectations from direct examination. As such, the V-ILI models have been trained to predict two relevant external corrosion condition metrics: (i) maximum depth (% of wall thickness), and (ii) number of external corrosion defects per square meter. These prediction metrics provide an in-field verification team with an expectation of what they are likely to find, alleviating the worry that they may have inadvertently missed something.

Three variations of V-ILI are utilized to predict the condition of the target pipeline. These models are defined as:

- **Model A:** A basic model, trained on a limited number of predictor variables with the intention of giving a general overview of the pipeline condition based mainly on trends that relate to pipeline design and construction.
- **Model B:** A more sophisticated model, with environmental predictor variables in addition to the basic design and construction inputs. As with Model A, the intention is to give a general overview of the pipeline condition but one that is more accurate than using design and construction information alone.
- **Model C:** A further extension of Model B that segments the pipeline and delivers a per-segment condition prediction. The predictor variables are the same as Model B – namely design, construction and environmental data. The intention is to predict which segments are likely to be in better or worse condition, reflecting the reality that many pipelines are in generally good condition and some have a few "bad" segments.

For a model to be trained and evaluated, sufficient metal loss ILI inspection data, representative of the target population that the V-ILI is attempting to predict, must be available. For example, if we are trying to predict the condition of uninspected pipeline installed during a certain period, then it is important that the IDW has enough of these groups to learn from. The same logic applies to other categories, such as external coating, pipe grade, location, etc. An imbalanced split of data between these groups (e.g., if the data is dominated by pipelines with a particular coating) can result in biases, with detrimental effects on the model's ability to successfully make predictions.

The IDW is a central repository containing in-line inspection data from tens of thousands of pipelines that ROSEN has inspected over multiple decades, including associated pipeline metadata. Table 1 summarizes the status of the IDW with respect to metal loss inspections at the time of writing; note that that it is continuously growing.

3. An Application of Virtual-ILI

The combined ECDA and V-ILI approach was investigated for a pipeline that we consider to be typical for the application of ECDA. It is a relatively short pipeline, just 7 km long. It crosses agricultural land and is a relatively high-pressure section of a gas distribution system – taking natural gas from a national transmission system and delivering it to a small town. The pipeline was installed in the mid-1970s; during its operational life, it had never been subjected to any inspection or pigging activities. A summary of the pipeline details is given in Table 2.

Prior to this study, there was some uncertainty regarding the condition of the pipeline. There had been no internal inspection, and the results of any historical aboveground surveys were unavailable, giving no clues as to the performance of the pipeline corrosion mitigation barriers, such as cathodic protection (CP). However, there was no physical or direct evidence that the pipeline was in a poor or degraded condition.

To gain an understanding of the pipeline, a phased approach was taken based on ECDA in combination with V-ILI to support the findings and prioritize excavation and direct examination sites.

Inspection runs	24,799
Number of pipelines	14,649
Number of pipe joints	66,604,244
Inspected length (km)	1,235,751
Number of external metal loss anomalies	22,332,886

Table 1: Integrity Data Warehouse summary (2023)

Description	High-Pressure Gas Distribution
Length	~7 km
Nominal Diameter	14" (377 mm)
Wall Thickness	9 mm
Pipe Grade	B
Design Pressure	38 barg
Construction Commissioning Date	Mid-1970s
Coating Type	Bitumen

Table 2: Pipeline summary

The Stage 1 pre-assessment concluded that, as the pipeline conveys dry sales gas for customer use, it was unlikely that internal corrosion was significant; therefore, efforts should be focused on an ECDA approach. A gap analysis showed that there was insufficient data to immediately move to Stage 3 and select locations to excavate and prove condition. The combination of the age of the pipeline (> 40 years) and a lack of reliable records indicated that the condition of the pipeline may be degraded. Experience suggests that diligent operators who maintain their pipelines in good condition also keep comprehensive records, so expert opinion is inclined to caution when records are missing.

In the next step, as part of Stage 2, a close interval protection survey (CIPS) and direct current voltage gradient (DCVG) survey were completed to gather information regarding the performance of the CP polarization and coating condition. While aboveground surveys are generally easier to complete than ILI or hydrotest, it is not a trivial undertaking, and achieving high-quality results requires the mobilization of an experienced team along with access to walk the pipeline route – which can also be difficult to arrange and costly.

In summary, no significant features were found in the CIPS and DCVG inspections, with the majority of coating defects considered to be minor, while all defects were found to satisfy the minimum protection criteria of -850m$_{VCSE}$. Only one coating defect was found to be significant, but it again satisfied the minimum protection criteria. Consequently, the indirect assessment process did not provide many locations of interest – other than the singular location driven by the significant DCVG indication. In this type of situation, the number of excavations required to prove the condition of the pipeline can be substantial, especially when attempting to prove an absence of corrosion defects, which is inherently more difficult than proving that corrosion is present.

In order to provide further context for the number of excavations required and to gain further confidence in the extent and severity of the corrosion, V-ILI was utilized. The aim was to further segment the pipeline to identify how many possible segments would be more likely to contain corrosion, whether they are particular segments, and how bad it could be based on the thousands of similar pipelines present in the IDW. This process enhances the confidence of the results from the direct assessment methodology and provides further justification of the pipeline condition.

Model C (geo-enriched and segmented) identified two segments:

- Segment 1, running from the start of the pipeline to approximately the 6-km point.
- Segment 2, comprising the remainder of the pipeline.

The segments are shown on a map below in Figure 2. Blue and red refer to Segments 1 and 2. Within the overall pipeline IDW, the dataset used for this study comprised data from 1,868 matched pipelines, considered to be a subset with good representation for the target pipeline. Included were pipelines from Europe and North America with construction years ranging from 1940 to 2020.

Using the machine learning algorithms of the matched data set, feature density within the target pipeline was predicted to be Class 3 (≥ 0.001 – ≤ 0.03 defects per m^2) with a confidence of 80% for both Segment 1 and Segment 2, suggesting a uniform low distribution of features along the whole length.

Maximum feature depth was predicted to be Class 2 (0% – 25% wall thickness) for Segment 1 with a confidence of 32%, and Class 3 (between 25% and 50% depth metal loss) for Segment 2 with a confidence of 39%. This suggests that any deeper defects are predicted to be found in Segment 2, the last 1 km of the pipeline. Note that the confidence in this wall loss prediction is low.

Reasons for the low confidence were not investigated as part of this study, but they could include:

- The training data was not sufficiently representative to provide a high-confidence match.
- The condition of the matched segments in the IDW data may have been highly variable.
- Similar segments in the IDW data may be close to the edge of the defined thresholds.

Following an analysis of the aboveground survey data and the V-ILI results, four excavation locations were chosen to give the best chance of finding any significant corrosion and best represent the possible data spread. The combination of V-ILI and aboveground surveys all suggested that it was unlikely that significant corrosion would be found at any location, but that the deepest defects should be present in Segment 2. Locations 1, 2 and 4, all in Segment 2, were considered to have the highest likelihood of having significant corrosion, while Location 3 was required in order to perform validation in Segment 1, where the likelihood of deep corrosion was considered to be lower. The distances and criteria are summarized in Table 3.

4. In-Field Results

4.1 Location 1

Contrary to the expected design, the coating was found to be a single-layer polyethylene (PE) tape, not bitumen (as per the data provided), casting further doubt on the system records. A single coating defect was noted due to soil loading of the wrap coupled with poor adhesion, as the coating peeled away easily; light surface corrosion was visible on the pipe surface, as well, likely as a result of poor surface preparation during the wrapping process as mill scale was removed and impregnated

Figure 2: Map showing pipeline route with Segment 1 in blue and Segment 2 in red, plus excavation locations

Location ID	Distance (m)	Segment	Comment
1	7,079	2	Highest combination of factors (CIPS, DCVG and V-ILI)
2	6,953	2	Highest DCVG defect, plus in V-ILI
3	1,147	1	Defect with low-level DCVG in Segment 1
4	6,384	2	Control site in V-ILI Segment 2

Table 3: Excavations resulting from the aboveground survey and V-ILI – location ID, associated distances and criteria

within the adhesive. The CP system was confirmed to be working, evidenced by the white hydroxide deposits beneath the coating. Crucially, there was no evidence of corrosion of any significant depth at the location, meeting expectations.

4.2 Location 2

The coating was again found to be a single-layer PE tape, not bitumen. Again, minor coating defects were noted. A single coating defect was found due to insufficient overlapping of the wrap at the 6 o'clock position, coupled with poor adhesion attributed to poor surface preparation during the coating application. The CP system was confirmed to be working, evidenced by the white hydroxide deposits beneath the coating. Crucially, there was once again no evidence of corrosion of any significant depth at the location.

4.3 Location 3

The coating at this location was a rubberized wrap system, not the expected bitumen or the PE tape seen at Locations 1 and 2, casting further doubt on the system records. Minor coating defects were discovered in addition to evidence of poor adhesion, as the coating peeled away easily, and light surface corrosion was visible on the pipe surface at the overlap areas. The CP system was working; however, it was clear some shielding had been present, leading to the formation of some minor corrosion pits < 1 mm deep (< 11% of wt).

4.4 Location 4

At the final location, the coating was confirmed to be the original 1970s bitumen. Given the relative age of the coating and initial appearances, it was found to be in good condition, with no coating defects present. The bitumen was found to be brittle and easily removed; however, this is to

Figure 3: General findings at Location 1

Figure 4: General findings at Location 2

Figure 5: General findings at Location 3

Figure 6: General findings at Location 4

be expected from bituminous coatings. Following removal of a small section of coating to confirm the condition beneath, the CP system was found to be functioning correctly, with a thin carbonate layer present on the surface and no evidence of corrosion of any significant depth.

In summary, there were minimal measurable corrosion defects at any of the four locations excavated. Three of the excavation sites were in the segment of the pipeline that V-ILI predicted to be in the worst condition, and two were at the locations of the most significant areas derived from the aboveground surveys, i.e., CIPS and DCVG.

5. Conclusions

The pipeline, despite its age and lack of historical data records, is in good condition and fit for future service,

Location ID	Distance (m)	Comment	Corrosion present?	Comment
1	7,079	Highest combination of factors	No significant features found	PE tape, some coating defects, no measurable corrosion
2	6,953	Highest DCVG defect	No significant features found	PE tape, some coating defects, no measurable corrosion
3	1,147	Defect with low-level DCVG	Minor corrosion defects found; < 1 mm depth (< 11% wt)	Rubberized wrap, coating defect at area of poor overlapping, possible shielding effect as few small corrosion pits were found
4	6,384	Control site	No significant features found	Bitumen, no coating defects, no measurable corrosion

Table 4: Summary of excavation results

supported by subsequent assessments to monitor for change.

Expert opinion alone would have concluded that the condition was uncertain and that potentially significant metal loss may be present due to the age of the pipeline and the lack of relevant data regarding the CP system and coating. In the absence of relevant and reliable historical data, the expert opinion was constrained and hence conservative.

The V-ILI model developed using machine learning based on a dataset of nearly 2,000 pipelines predicted the condition to be fair. That is, some corrosion (0.001 to 0.03 features per m^2, or up to 1 feature every 2.5 pipe joints) was predicted, and maximum depths of 25% to 50% wall thickness were predicted for the final 1 km of the pipeline. Excavations in locations where significant corrosion was most likely (according to the V-ILI and ECDA models) – but still low probability – did find some coating flaws and a few surface blemishes. However, no significant corrosion features were seen, the maximum being < 11% wt. Therefore, the overall condition of the pipeline is expected to be good, an assessment backed up by correlation with field excavations of both ECDA and V-ILI predictions.

The models to predict pipeline condition developed using machine learning and an appropriate sample taken from the IDW were useful in supporting the ECDA process, most notably as part of the pre-assessment with minimal initial data, through interpretation of aboveground survey results, and the selection and completion of relevant excavations. In this way, V-ILI was shown to be a useful tool to improve confidence in the examination results – as being representative of the pipeline.

The integration of V-ILI into an ECDA process provides data to back up the expertise and opinions of pipeline integrity/corrosion subject matter experts, strengthening the position of the experts and providing them with an additional input that can be used when historical inspection or survey data is sparse. This is especially true in the case of pipelines where minimal corrosion may be present, as proving the absence of corrosion can be more challenging than identifying its presence.

6. Further Work

The initial results of integrating V-ILI into the ECDA process as a screening tool show promise, especially in terms of boosting confidence in the ECDA results when limited data is available. The integration of additional ILI data into the IDW increases the variety and amount of relevant pipeline data from different and similar cases, also expanding the capability of V-ILI to deliver more accurate predictions. ROSEN will be further developing not only the model algorithms but also how V-ILI can be integrated into the core of the ECDA process.

References

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