



#### FOR ALL WET CORROSION ISSUES

Welcome to MCF – Marine Corrosion Forum / ICorr – Institute of Corrosion (ABZ), 2021 April Webinars.





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Institute of Corrosion (ABZ) and MCF partnering with:

ROSEN

• 27th April 2021







## "Virtual In-Line Inspection for Corrosion Management in Un-piggable Pipelines"

#### **ROSEN -** Michael Smith | Senior Engineer and Data Scientist 27th April 2021

# About Virtual ILI

- Over the past 30 years, ILI data has been collected from all around the world. Although pipelines are diverse in their characteristics, many share similar risk profiles for common pipeline threats such as external and internal corrosion. This has led the industry naturally towards machine learning as a complementary corrosion monitoring solution for pipelines that cannot be inspected using ILI.
- For a given uninspected pipeline, we can source data for similar inspected pipelines and use machine learning algorithms to generate predictive models. The results of a "Virtual ILI" create clear justification for planning actual inspections or maintenance in challenging pipelines.



**ROSEN -** Michael Smith | Senior Engineer and Data Scientist



 Selection of Questions to ROSEN, Post-Presentation 27/04/2021

- Q1. When discussing the Low-Res model, is this for uninspected or un-inspectable (non-piggable) pipelines?
- A1. Can use for both inspected / uninspected lines. Could also be used between inspections (with different techniques).

- Q2. What ILI type of information are you using for these comparisons for the machine learning. Is it taken from UT and MFL pigs? It is widely known that MFL pigs, due to the nature of the measurement, over-estimates the wall loss, and external verification with UT has confirmed this. 90% of the time, the largest defect has the largest error. How do you combat this when using that data for machine learning?
- A2. The training data is predominantly MFL. Agreed that in a large, *homogeneous* sample of anomaly measurements, the maximum measured depth tends to be associated with the highest positive error. However, this is a statistical effect observed with *any* imperfect measurement technology with random errors, not just MFL.
- Note that not all anomaly populations are homogeneous (especially with external corrosion) and across 10,000 pipelines, we see many cases where the maximum depth is accurate and represents a unique, localised corrosion environment. If we assume all maxima are overestimated then our models will never be capable of predicting extreme values, which would be unsafe.

- Q3. How do you integrate the effectiveness of the CP design, presence of stray currents, etc. in your model?
- A3. Not incorporated as yet but can adapt and list all threats, then need to turn into variables.

• Q4. How do you judge/ensure the quality of this data? I am particularly addressing CP data, as I see a range of high quality, accurate data to data that is not worth the paper it was written on, or the memory space it took?

• A4. The ROSEN Data Warehouse has been built over 3 yrs. Must always be careful not to apply own bias.

- Q5. Have you tried correlating the predicted locations in the high resolution model with worst locations predicted by ECDA (External Corrosion Direct Assessment) \* methods?
- A5. No, we have not done so as yet.
- \* ECDA improves safety of pipelines through assessing and reducing the impact of

external corrosion on **pipeline** integrity. This process prevents corrosion defects proactively from growing to a size that may ultimately hampers a **pipeline's** structural integrity by: Locating and addressing corrosion activity.

- Q6. Do you consider pertinent historic internal process management KPI data when correlating the corrosion trends?
- A6. Not as yet but have included indirectly into Model.
  Operator variables do have predictive powers. Country and
  Op. Budgets can be a factor though.

 Q7. The presentation discusses machine learning applied to external pipeline defects. Would this also apply to internal pipeline defects? If yes, what variables would be considered [would anomaly density still come into play]?

• A7. In general, inputs for Internal corrosion – include: composition temp., pres. Etc. + orientation.

- Q8. Have you collected any data on the quality, particle size and compaction of pipe backfill? This can have a big impact on CP performance and rainfall/water flow in the pipe trench?
- A8. Good suggestion, not as yet. Difficult to get this level of data. Closest is soil type variable (from published soil maps), or sampling if exists.

• Q9. Two questions in terms of predicting corrosion rate. How will the high-resolution model of anomaly density be applied for corrosion rate predicting? What is the time frequency or how long is the time step of predicting value?

 A9. A complex question, we have predicted this aspect in a different model, specific for this purpose. Always need to be able to Train the Assessment Model. Some previous assumptions used have been questionable such as 'half-life' approaches.

- Q10. How has the model incorporated accelerated corrosion phenomena that is not challenging to predict and dynamic in nature such as stray current external phenomena and AC interference?
- A10. Machine learning is not so good for predicting rare / extreme events. A much larger data set is required to get close to such predictions.
- See Q20 <u>below</u>.

- Q11. With regard to your "variable importance" slides. Most of the parameters are single values (e.g. date of installation, average annual rainfall). However, CP potential is not fixed. As lines get older there is an increasing probability that they will have been subject to more varied periods of CP, or even periods when the CP systems were not working. How does the system deal with such time-dependent parameters?
- A11. An excellent question and this is subject of a separate research project presently. There are also seasonality and ageing effects for sure.

- Q12. Has this technique been used for internal corrosion in pipelines? if so, how well does it compare with external corrosion?
- A12. Yes it has been used and is comparable but using different variables and have other Internal Models of course.
   Bayesian Models can also be used <u>in conjunction</u> with NORSOK etc.
- Need to take great care when using Bayesian Models alone.

- Q13. Can we predict the anomaly type as mentioned in pipeline operator forum and other references?
- A13. Yes, will get good performance for corroded area.

- Q14. Great and interesting presentation. Have you tested and verified with outcome of the machine learning study with real inspection?
- A14. Our models are verified from ILI's of older pipelines, not for new pipelines, as yet.

• Q15. What is the accuracy of the model?

• A15. Accuracies are as quoted in the presentation slides.

- Q16. Would the outcome be very different with unsupervised machine learning?
- A16. No, this would not be a good idea. You can use unsupervised machine learning however, specifically for clustering of data for a specific parameter.

- Q17. How about AC corrosion, we have experience of unpiggable' pipe failure and what are the parameters? CP will not be factored fully, as it can induce more AC corrosion?
- A17. Parameters in AC corrosion models would include proximity to AC source (induction/conduction), coating type, AC voltage and current density (requires coating defect size). We have some of these in the model but not others. We intend to improve this over time as data availability increases.

- Q18. Can the model allow for older pipelines with coating systems which are known to have issues with dis-bonded coatings?
- A18. Yes we have plenty of examples of older pipelines with coating systems susceptible to dis-bondment.

- Q19. Have you investigated using cumulative Annual precipitation and pipeline life duration?
- A19. Indirectly, since *mean annual precipitation* is calculated using the cumulative rainfall over a given time period.
- Pipeline life is also there as a variable.

- Q20. As I have always found that no 2 pipelines are the same... Can we assume the model is suitable for non-stray current pipelines for now and look at the future models to be inclusive of these dynamic and rare parameters ....all sounds promising?
- A20. Agreed that no two pipelines are identical, but the majority of corrosion mechanisms still produce a surprisingly narrow range of sizes and rates. It's unclear at this stage how much additional performance we'll get from "dynamic and rare" parameters, but we'll still try.
- Maybe we would see more success with predicting extreme values.

# THANK YOU FOR ATTENDING

This Webinar was brought to you by MCF working in partnership with ICorr Aberdeen and **ROSEN**.