Identifying and Characterizing Corrosion Morphologies More Effectively with Triaxial MFL Signal Analysis

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Abstract

Magnetic Flux Leakage (MFL) inspection was the first technology introduced in the 1980's to routinely inspect oil and gas pipelines for corrosion defects, and today it remains the most trusted In-line Inspection (ILI) technology for that purpose. Thousands of MFL inspections are carried out by ILI vendors each year ensuring pipeline operators can effectively manage their corrosion integrity programs.

Since the introduction of high-resolution axial MFL inspection vehicles, there has been a substantial number of improvements in capabilities. These include inertial mapping units (IMU), speed control, increased sensor density and combination sensing (geometric, eddy current, transverse MFL and triaxial MFL measurement).

Even with these advances, surprisingly most MFL inspections only measure and use one of three components of magnetic flux field leakage that occur at a corrosion feature when magnetized by the inspection tool at a localised thinning of the pipe wall. However, it is well proven that different corrosion morphologies will trigger significantly different leakage in these components. These characteristic signatures consequently provide an additional and robust means to identify corrosion profiles and interactions that in many cases are not detectable or distinguishable when using only a single axis – no matter how high the sensing resolution the inspection tool may have. Optimising sensor resolution in combination with measuring all three leakage components offers clear advantages, particularly when defect morphologies become challenging.

This paper will provide a deeper insight as to how the three independent leakage components provide unique identifiers that can be used to accurately size pinholes, axial and circumferential slotting, and importantly de-construct complex morphologies and be used more effectively in the analysis process to improve POD, POI, and POS. These identifiers not only ensure correct corrosion interpretation, but also that these defect types are identified correctly within the often hundreds of thousands of features within many miles of pipeline.

The paper will conclude with a demonstration of how, in combination with monitoring of data accuracy for every validated inspection conducted, the adoption of data accuracy results as a key performance indicator can be effectively employed to target and drive continuous improvement of even the highest performing inspection technologies.

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Introduction

The in-line inspection industry has measured the success of an in-line inspection service in the same way since the introduction of the *Pipeline Operators Forum defect classifications* and the *API 1163* definitions on how to measure statistical population performance. However, these traditional methods pose challenges to pipeline operators when real life situations occur, which do not fit into standard dimension class categories.
Let us consider the following two familiar questions:

- *"The corrosion on my pipeline does not fall into the simplified 7 POF categories; how do I measure performance on complexity of defects like pit in pit and other interacting defect?"*

- *"It is great that the ILI tool was within specification on the 98 features from infield verification on my pipeline, but I have 2 outliers, not in specification which nearly caused a leak. How do I manage this effectively?"*

If technology is only challenged to conform to this overall statistical approach, then the opportunity to truly solve real world problems and take advantage of technological improvements is lost.

To fully drive change and improve quality and ultimately safety, then we must look at the problem/challenge in a multi-phased approach [Figure 1]:

1. Understand the limitations of a simplified specification.
2. Collect the ILI data you need.
3. Measure overall performance.
4. Measure Performance on:
    - Safety outliers – under-calling defect significance (potential of leak)
    - Resource outliers – over-calling defect significance (unnecessary digs)
5. Combine Overall Performance with Safety/Resource outliers = Data Accuracy Score
6. Utilize Artificial Intelligence to push the boundaries of modelling of defects.
7. Circle back to multiple previous steps.

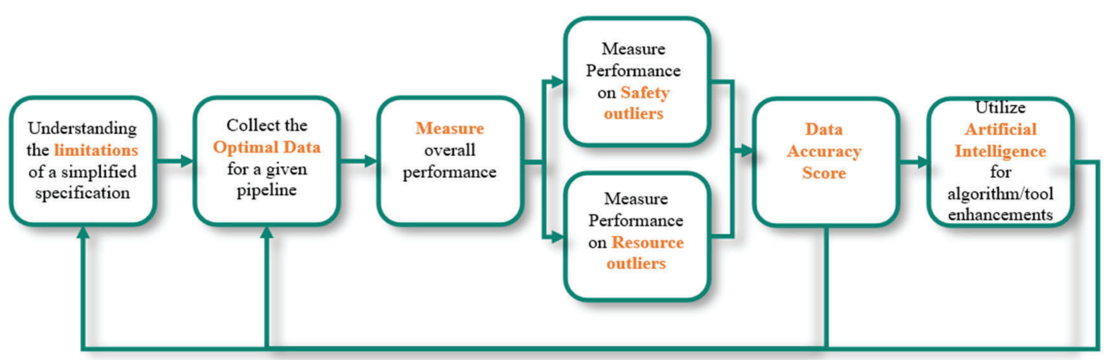

Figure 1: Baker Hughes continuous improvement workflow

Within this paper we will revisit some of the principal benefits of triaxial data and how deep learning can be utilized effectively while also looking at how Baker Hughes is utilizing a dig database and Data Accuracy Score

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to ensure that technology advancements are focused on what will have the most impact to dig efficiency and effectiveness.

1. Understanding the limitations of a simplified specification

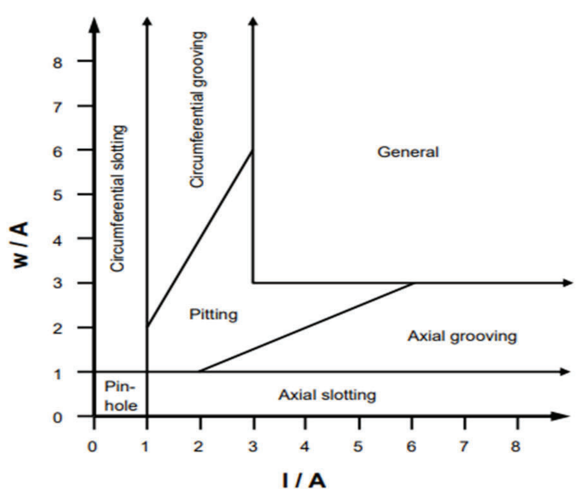
Pipeline corrosion can manifest in various shapes and sizes, both internally and externally. For many years, the industry has utilized the Pipeline Operators Forum (POF) specification to categorize defects based on their length and width (Figure 2). This standardized approach is globally recognized and widely used.

However, when corrosion involves intricate features (as it often does) like defects within defects, intersecting axial slots or defects fully enclosed within background corrosion, the situation becomes more complex. These types of defects are challenging to assess correctly and do not fit easily into these simple feature types defined solely by length and width. Operators should be aware that simplified specifications might have been based on idealized parabolic shapes, potentially misrepresenting the true nature of complex corrosion profiles.

Complex corrosion morphologies can pose significant challenges for both axial and circumferential Magnetic Flux Leakage (MFL-A & MFL-C) tools. Pipeline operators dealing with such corrosion face two primary risks:

1. Safety Outliers: Underestimating the severity of defects, potentially leading to leaks.
2. Resource Outliers: Overestimating the severity of defects, resulting in unnecessary excavations.

Baker Hughes addresses these challenges by leveraging the additional information available with triaxial MFL data. Unlike standard axial MFL, which provides a single measurement, triaxial MFL offers three measurements: axial, radial, and transverse. This additional data enables more accurate defect characterization and assessment, mitigating the risks associated with complex corrosion profiles.



The geometrical parameter A is linked to the NDE methods in the following manner:

- If t < 10 mm then A = 10 mm
- If t ≥ 10 mm then A = t

Figure 2: POF metal loss categories

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2. Collect the data you need - Benefits of Triaxial Hall Effect Sensors.

Since “Leakage” is a Vector quantity, each sensor measures the 3 orthogonal components of this vector. By doing so, the tool captures 3 different responses from a feature, maximizing the possibilities to properly understand its real morphology. The sizing algorithms predict the actual feature’s dimensions, combining variables such as wall thickness (WT), speed, and magnetic flux leakage volumetric characteristics. The additional insight given by the independent triaxial sensors’ readings becomes relevant as it allows better determination of critical measures needed to correctly parameterize interacting signals in complex defect morphologies or for defect shapes found challenging with single axis measurement. Axial slots and pinholes within larger areas for corrosion would be examples.

The same sensor head can record the magnetic flux leakage resulting from wall loss by the Axial, Radial, Transverse vector components plus the Eddy Current for IDOD [Figure 3].

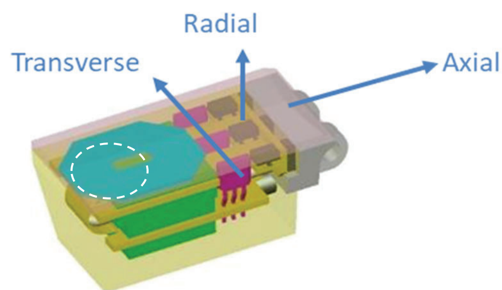

Figure 3 - High density multiple "Triax" sensor head.

To gain a deeper understanding of how the three independent leakage components offer unique identifiers, we will explore both theoretical and practical applications.

Figure 4 illustrates the recorded and displayed data for each component of the magnetic flux leakage vector.

Axial

- Measured along the pipe
- Sensitive to “Volumetric” losses
- Measure nominal field strength

Radial

- Measured out/in from center
- Highest sensitivity to changes in depth
- Identifies start and end of features

Transverse

- Measured circumferentially around pipe
- Added sensitivity to in-plane shape
- Improved width measures and ID of background corrosion.

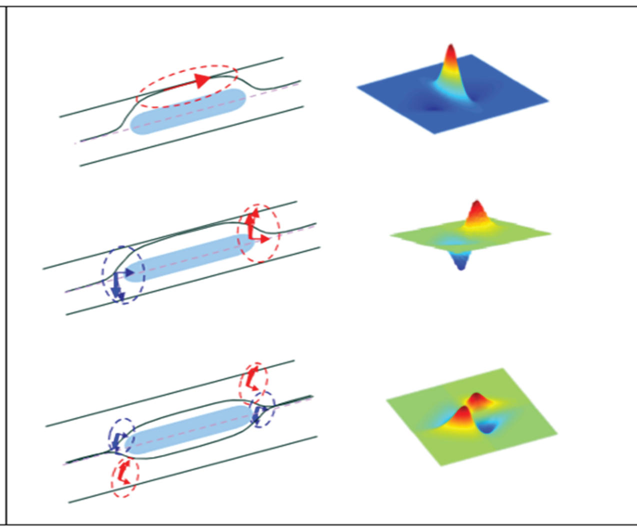

Figure 4 - What is recorded and displayed for each component of the magnetic flux leakage vector

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Now, we will present some examples (from basic theoretical schemes to real complex case studies), demonstrating how important it is to de-construct complex morphologies and use this in the analysis process to improve POD, POI, and POS. more effectively These identifiers not only ensure correct corrosion interpretation, but also that these defect types are identified correctly within the often hundreds of thousands of features within many miles of pipeline.

The first example is from a real spool test piece added to an offshore line for tool validation purposes. In the short 10ft piece of pipe, metal loss defects following different morphologies were machined. The defect highlighted is an axial slot that can be challenging to conventional axial only MFL tools. However, the dimensions of the leakage response such as length, width and depth have been accurately measured by the radial sensors but complemented by Axial and Transverse components. [Figure 5]

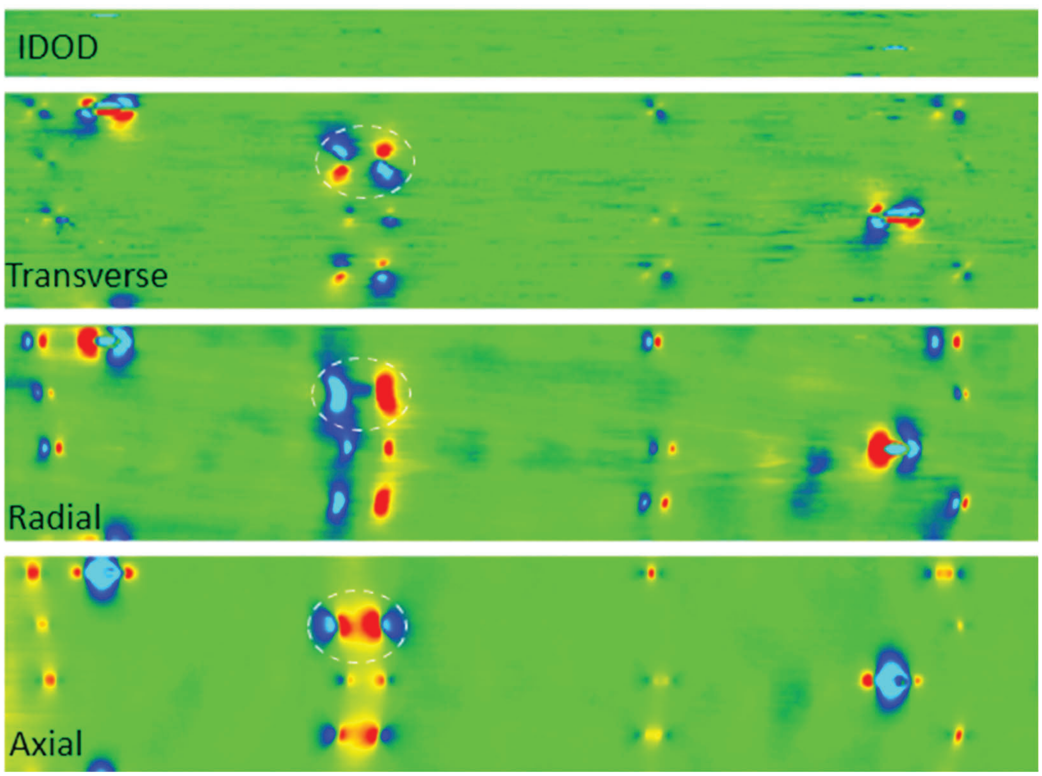

Figure 5 - MFL Triaxial Sensor Data in an offshore validation spool (MagneScan™ tool)

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The axial component of the signal has been evaluated and well understood through the sizing algorithms for more than 30 years, but it is the radial and transverse components which provide a considerable advantage to correct interpretation of interacting anomalies, especially when multiple defects interact with each other, and even more in axially oriented morphologies.

The radial component of the flux leakage is usually shown as bipolar signals in ILI data. In the following examples, we can see how the signal amplitude of the interacting A and B poles help to de-construct the morphology of the real shape of the defect. The A pole represents the start of defect, where the flux leakage starts (or changes) represented by the yellow to red shading and the B pole represents the end of a defect, where the flux leakage returns (Partially or fully) represented by the green to blue shading.

It becomes clear how to differentiate individual interacting pits from pit within pit or complex interacting corrosion [Figure 6].

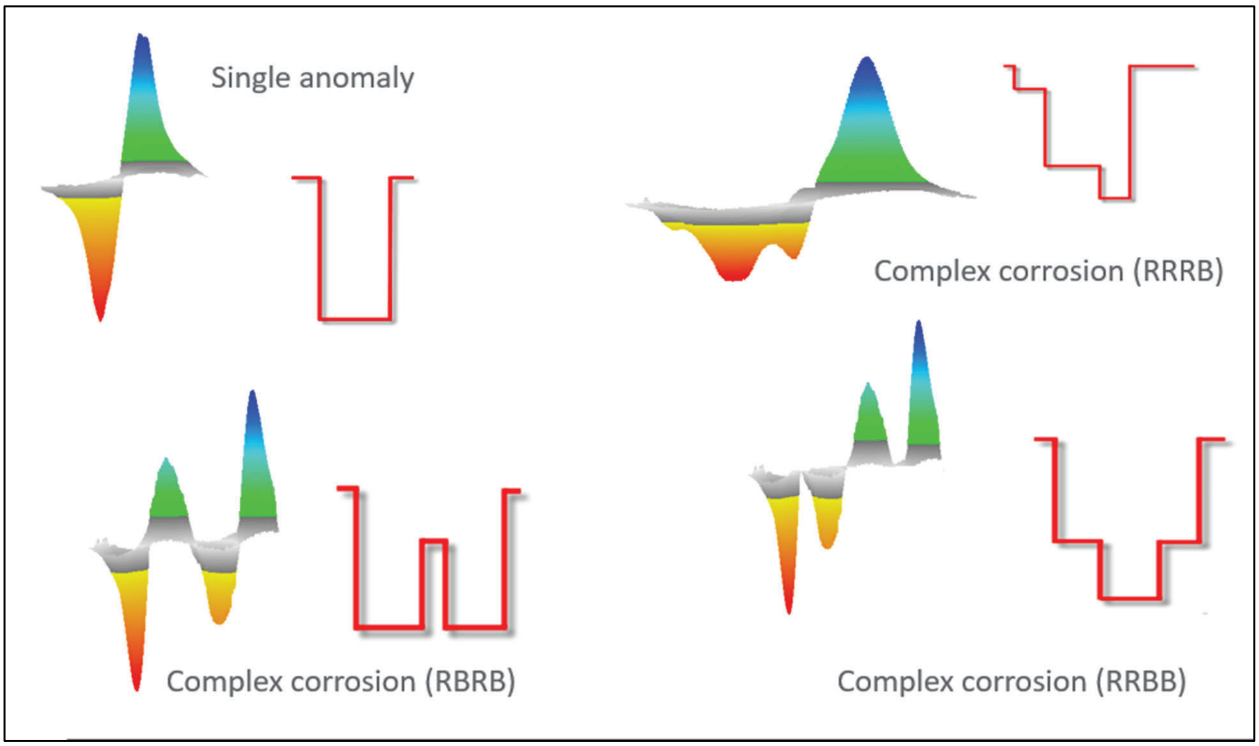

Figure 6 - Radial Component Readings in single and complex anomalies.

The 3-component signals have a direct impact achieving higher confidence in the predicted depth, length, and width of a given anomaly, especially when we compare to single axis MFL performance on complex corrosion or challenging morphologies. This has been demonstrated through the thousands of features collected every year, allowing Baker Hughes to provide best in class POD, POI and POS for pinholes, axial and circumferential slots. (REF 3.)

The following case study is from a recent Industry Collaboration Project, where axial slot-like features were fabricated within areas of general corrosion. These types of morphologies are commonly seen in the field associated with the long seam and classified as Selective Seam Weld Corrosion (SSWC). With this

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opportunity we can appreciate the difficulties that the conventional axial only MFL tools will have, and how having three responses at every given feature helps to better understand the actual morphology of the defect through a better signal measurement [Figure 7].

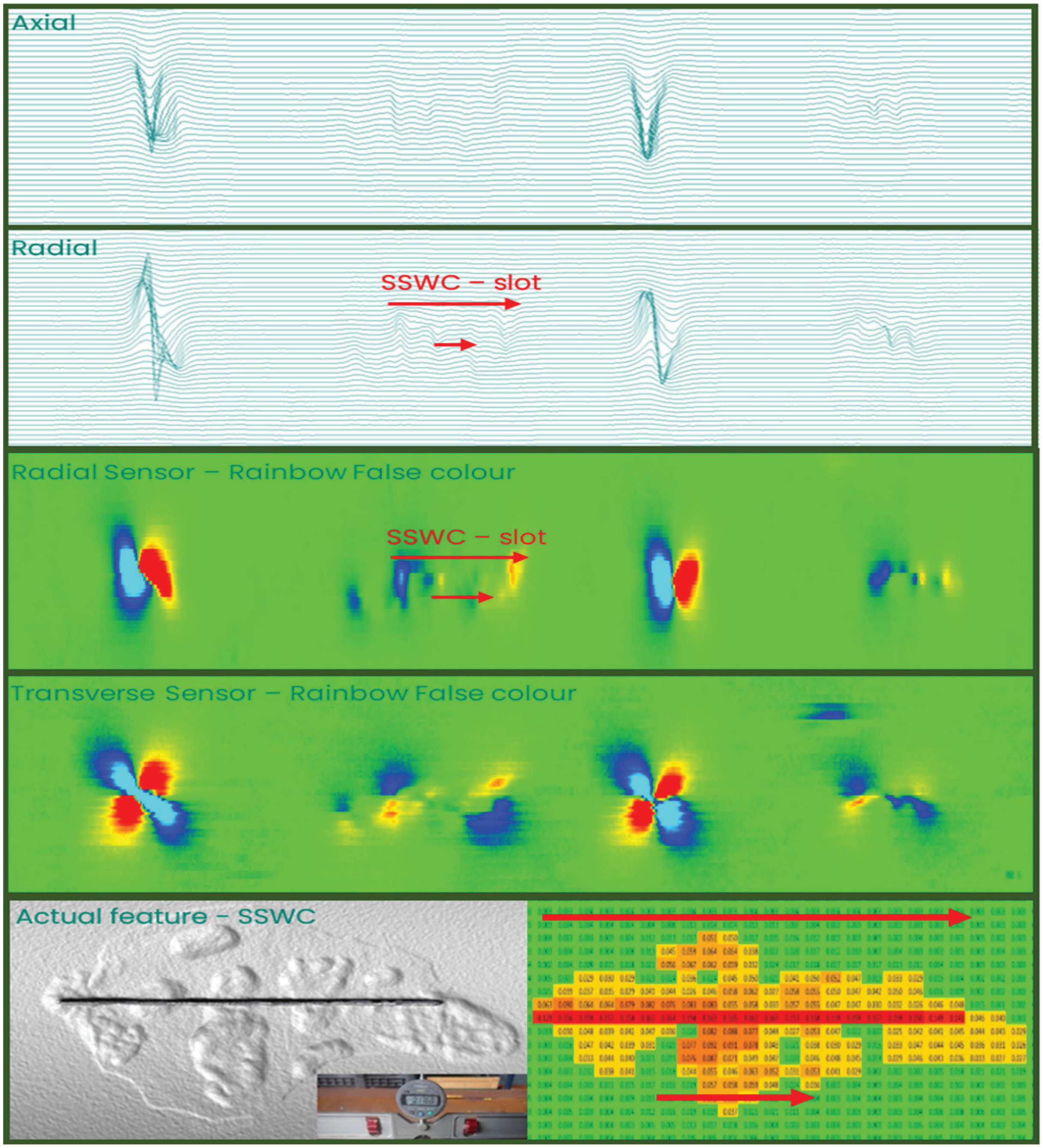

Figure 7 - MFL Triaxial Sensor Data recording Axial Slot feature within and area of General Corrosion (MagneScan™ tool)

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When we talk about collecting the data you need, we should not stop at what is recorded but how this information is displayed is to be evaluated in complex corrosion situations by the ILI data analysts and Pipeline Integrity engineers. In this last example, we will see how the Axial and Radial sensor readings overlapped in the same view can help the data analysis process to de-construct overly complex areas of corrosion as can be appreciated in the Laserscan data collected in the field [Figure 8].

This scenario represents the deepest points within the Laserscan data as pitting corrosion located within an axial area of corrosion.

Due to the complexity of the area of corrosion, the axial extent would be unlikely to be correctly accounted for with axial data only and result in an under-call. But by utilizing the triaxial sensor data, applying background corrosion, and remaining WT techniques, the technology was able to assess the deepest points as 69%wt with a total length of 26.1in by 8.7in width within 10% of the actual measurements in field.

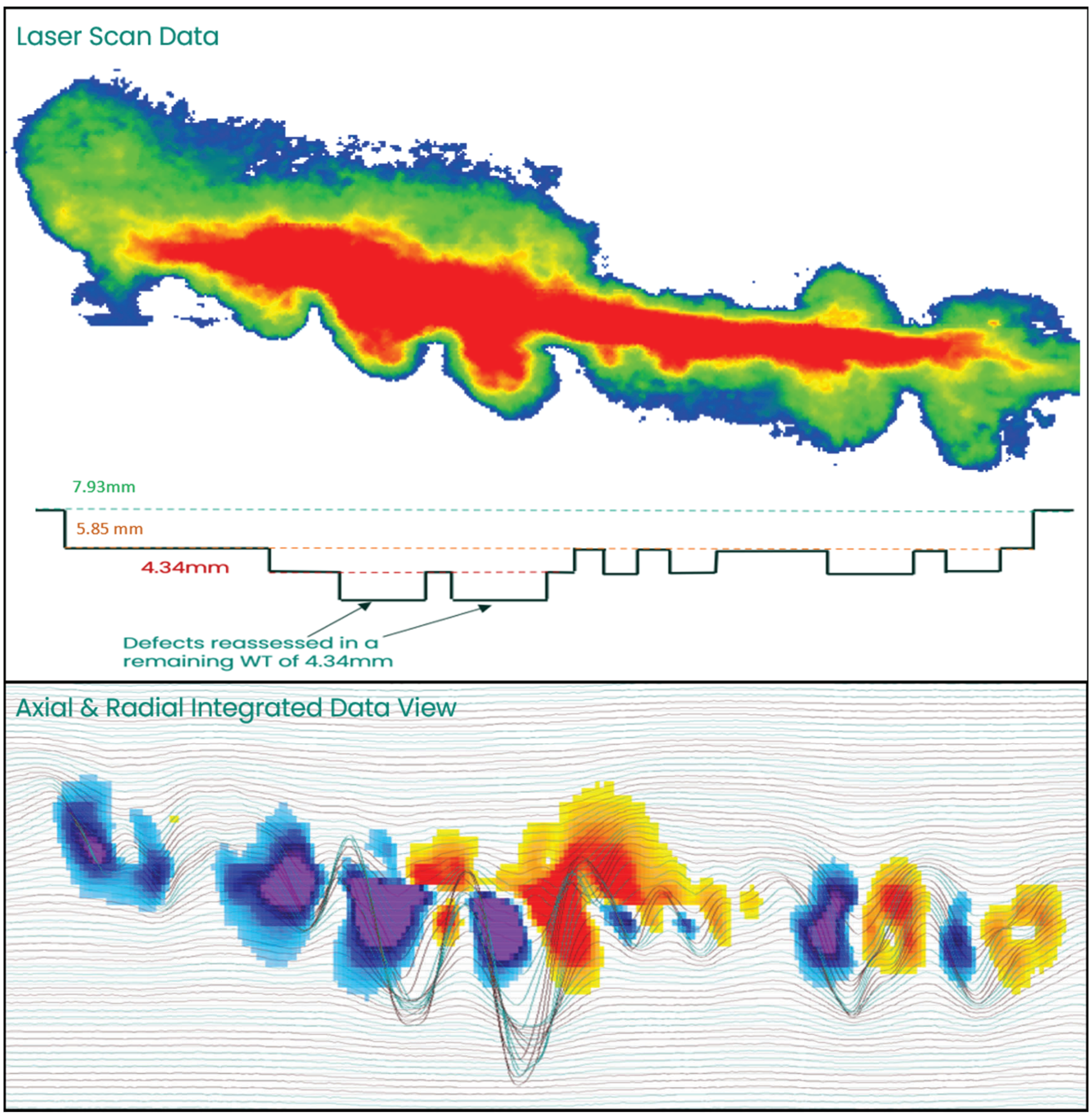

Figure 8 - MFL Triaxial sensor overlap View (MagneScan™ tool)

3. Measure overall performance

Pipeline Operators must collect and provide infield inspection data to ILI vendors to enable the development and improvement of ILI services.

The standard format for comparing infield dig data with the ILI reported data is the form of a depth unity plot. These are typically broken down further to the different POF categories. These unity plots are understood and utilized extensively by both Operators and ILI vendors.

"Performance to specification" is calculated by the API 1163 Level 2 assessment methodology.

- Calculation of standard published metrics (POD, POI, POS). [Figure 9]
- Specification verification.

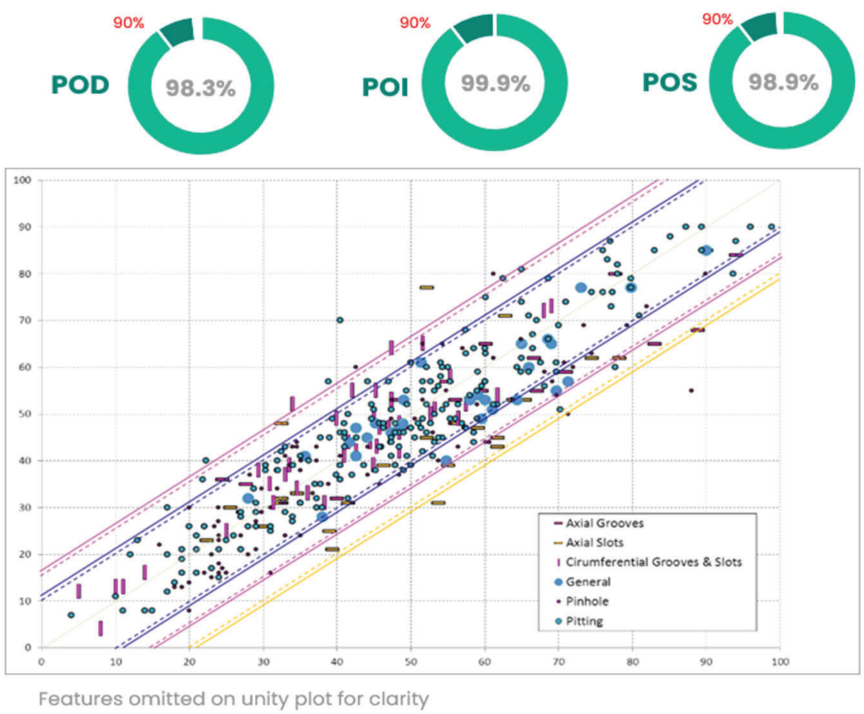

Figure 9 - Depth based Unity Plot showing standard performance specification metrics (12" MagneScan™ tool)

However useful unity plots are for gauging general trending performance, they do not offer insights into "real" challenges facing both the infield data collection and the ILI inspection technology challenges. As discussed in Section 1, the performance on a unity plot is linked to the standard ILI specifications; however, it does not look at the complex real-world situations found with corrosion on a pipeline.

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Both operators and ILI vendors need to ask the question: if the population is 98% within specification but there is a leak on the pipeline, is that really an acceptable outcome?

Pipeline Operators are focused on ensuring zero failures with cost effective repair programs. To do that they need to minimize both:

- Safety outliers – under-calling defect significance (potential of leak/rupture)
- Resource outliers – over-calling defect significance (unnecessary digs)

In the example below the overall statistical performance to the contract specification is achieved [Figure 10].

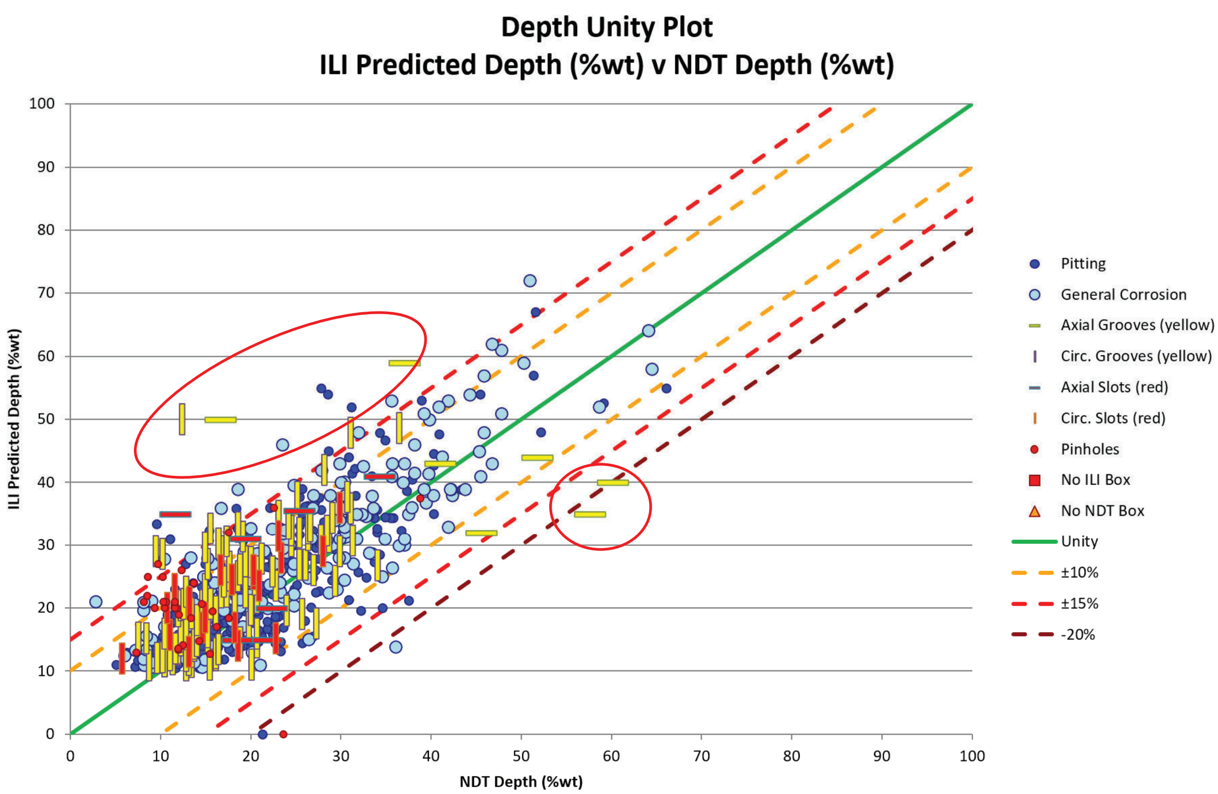

Figure 10 - MFL Depth unity plot

However, all operators would agree that even though the contract specification was achieved, they would have concerns about the range of outliers (in red). Therefore, the challenge is twofold:

- The general population must be statistically significantly correct.
- The number of outliers needs to be limited.

By only looking at overall statistical performance, operators will not challenge ILI vendors to improve and therefore accept some safety risk (managed through conservatism in dig criteria) and potentially unnecessary cost. Conversely, if ILI vendors do not track and investigate the causes of outliers, then they risk not taking the technology capability to entitlement and more importantly although in specification may not providing the service really needed to optimize integrity programs.

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4. Measure Data Accuracy Score (DAS = Overall performance + Safety & Resource performance)

To ensure that data driven performance improvements are proactively made, Baker Hughes has implemented an internal key performance indicator "Data Accuracy Score" (DAS) that focuses directly on what matters to the users of the inspection technology.

Data Accuracy Score is a measure believed to be more indicative of when inspection dig results are truly meeting user expectation. It considers two performance criteria, "Performance to Specification" and "Outlier Performance". It is not considered good enough to simply meet published specifications. This is key, because it removes the effects of favorable statistics and highlights unwanted outlier performance that may not present a significant customer concern but to the ILI vendor an opportunity for improvement.

The principle is the same for all technologies, but this paper specifically focusses on MFL data [Figure 11].

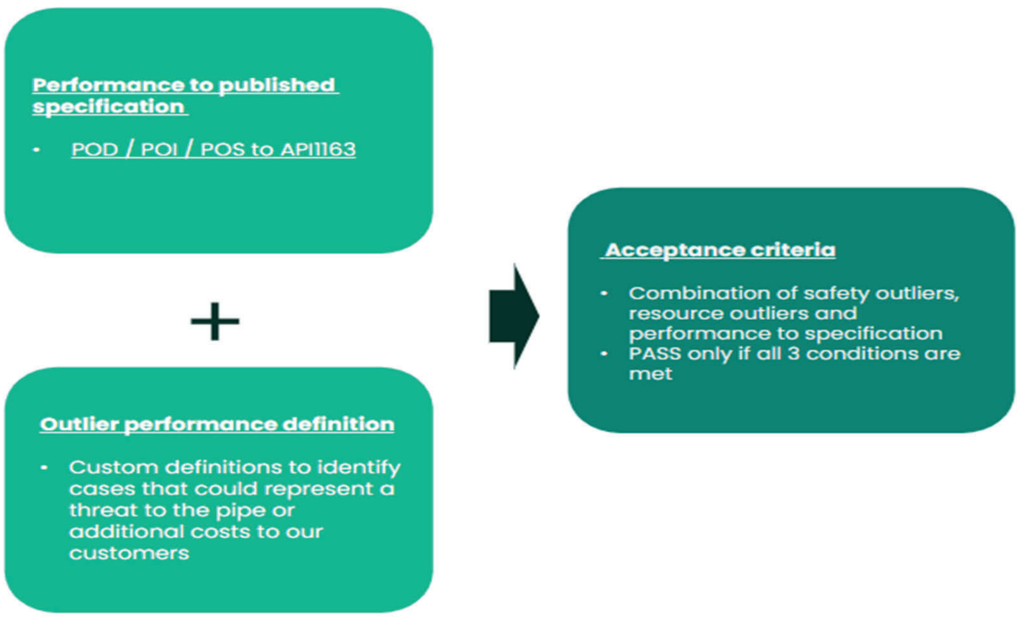

Figure 11 - Baker Hughes Data Accuracy Score Criteria

The Data Accuracy Score combines the Specification Performance with the Outlier Performance to give an overall score.

1) "Performance to specification" is calculated by the API 1163 Level 2 assessment methodology.
    - Calculation of standard published metrics (POD, POI, POS).
    - Specification verification.
2) "Outlier performance" is calculated based on prescribed definitions of Safety and Resource outliers that were determined based on client feedback and as a way to identify outliers (previously not considered) that could represent either a threat to the pipe or additional cost to our clients.
    - Independent Pass/Fail for Safety and Resource Outlier is calculated.

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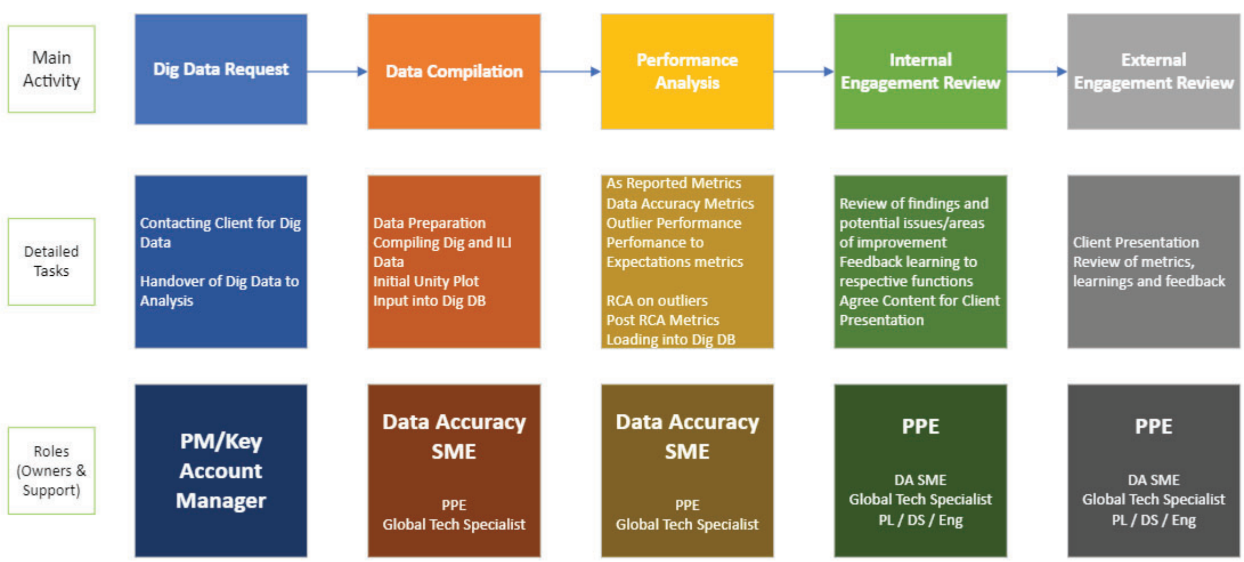
By ensuring that each of the Specification, Safety and Resource performance criteria must each individually "pass" to achieve an overall Segment "Pass" a considerably more stringent process of triggering internal performance review is achieved.

Even though a lagging indicator, the advantages of the adoption of the DAS metric is two-fold. Firstly, from a customer perspective an assurance that performance is being monitored and from a perspective of what matters and not just contractual obligation. Secondly, and more importantly, it provides a means to promote dig feedback, assess and trend performance and identify common areas for targeted process, algorithm, or technology refinement.

Given the multiple data, 1000's of runs conducted, and many forms of dig data an investment in a comprehensive infrastructure is necessary to connect the multiple processes together, store analysis results, raw signals, analysis investigations to allow effective trending and improvements. Baker Hughes has implemented a cloud-based system linked to a Performance Database to streamline the integration, alignment, and storage of signal data, with analysis and dig results, associate causes of performance issues (at the defect level) and provide the data presentation and mining tools to directly identify trends, causes and target improvements.

The Data Accuracy Score is managed within Baker Hughes through a rigorous process and supported with key resources to ensure that focus areas are identified for technology and process developments to improve and advance the ILI technology and results to deal with the complex situations customers face [Figure 12].



- **PPE – Platform Performance Engineer**
- **DA – Data Analysis**
- **PL – Product Line Management**
- **DS – Data Science**
- **Eng – Engineering**

Figure 12 - Baker Hughes Action owners

5. Utilizing Artificial Intelligence to push the boundaries

In parallel to the advanced analysis possibilities with triaxial data and the associated benefits of a robust process for monitoring and driving inspection results accuracy improvement, advanced data analytics techniques are playing a larger and larger role in potentially step changing MFL accuracy performance.

Baker Hughes has been utilizing machine learning techniques since the late 1990's for MFL sizing. In 2019 investigations were directed to using more capable Deep Learning techniques given the vast quantities of truth data held in our performance database.

The output of one such model is shown in Figure 15 where a set of laser-mapped defects is shown beside an output of one of the deep learned models.

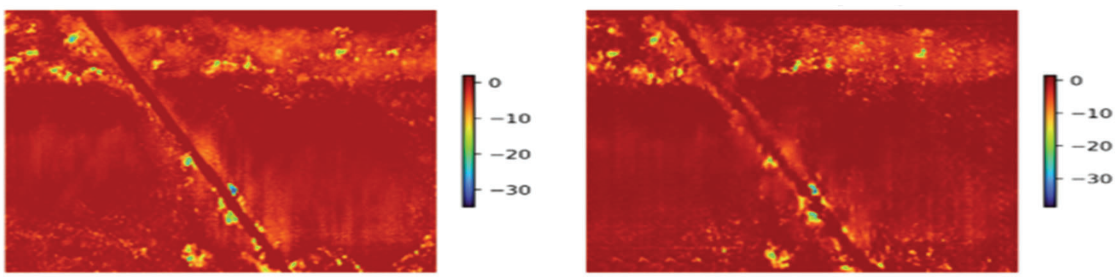


Figure 15 – Laser-mapped defects and the output of a generative AI deep learned model for the same area. An example of laser (left) and predicted laser profile (right)

Considerable advancements have been made in firstly developing the techniques to establish the huge computing power needed to run deep learning models on the vast quantities of raw ILI data collected on an entire pipeline segment, in a time frame acceptable for typical analysis report delivery. Secondly, developing models that can accurately and reliably establish the true corrosion profile that will result in optimal depth and burst pressure performance. (REF 4.) Examples of such performance capabilities are presented in Figures 16 and 17.

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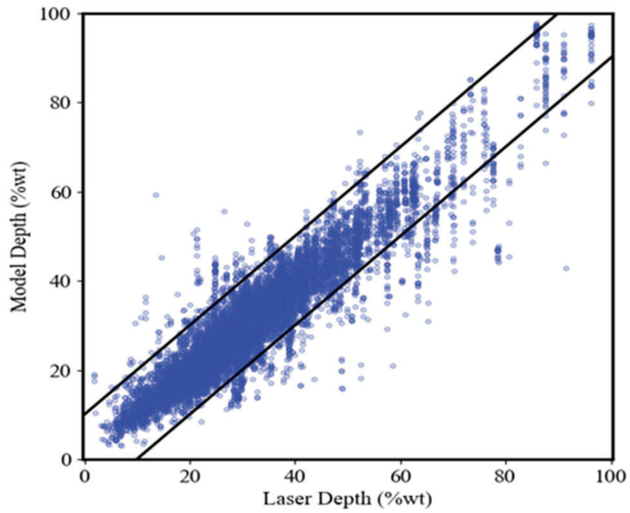

Figure 16 - Unity plot comparing the depths of defects found in measured laser data and in the deep-learning model output.

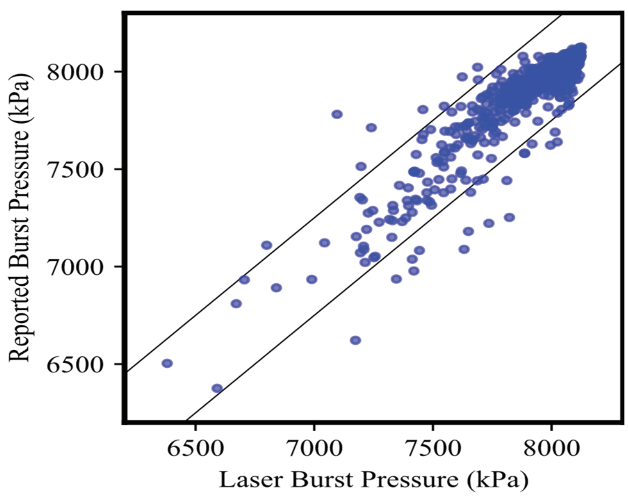

Figure 17 - Unity plot of burst pressures determined from the measured laser profile and the reported defects from the current sizing method.

6. Closing the loop for continuous improvement

The final stage and the most important stage to develop an environment of continuous learning is revisiting prior stages of:

1. Understanding the limitations within the specifications
2. Collecting the correct ILI Data

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Any learning should be implemented in these key stages, this could be expanding the specifications to new sensing or data volumes on the inspection's vehicles [Figure 18].

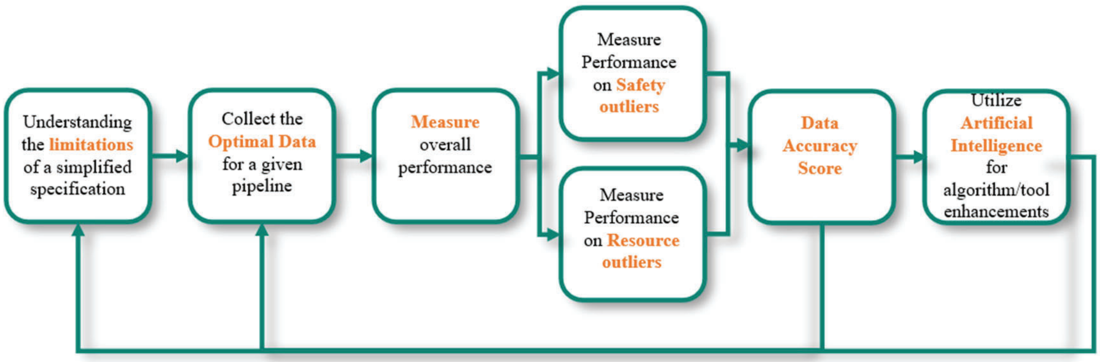

Figure 18: Baker Hughes Continuous Improvement Workflow

It is essential that this process is embedded into how we develop technology and techniques to ensure the quality, safety and value of ILI inspection data continues to increase.

Advancements through AI and optimizing tool design will highlight new defect morphologies which are not covered by the simplified specifications. These advancements need to be differentiated from the standard specification.

Conclusions

By understanding that simplified specifications cannot cover all aspects of complexity of defects within the pipeline, this paper has demonstrated that a traditional statical comparison to standard specifications is not sufficient to drive meaningful technological advancements.

Only by combining both the traditional statistical comparison of the population in conjunction with Safety and Resource outlier statistics and by providing additional data to allow more precise characterization of challenging features can you have a meaningful understanding to fuel innovation in Artificial Intelligence and inspection tool performance improvements.

Baker Hughes tracking of Data Accuracy Score leverages this principle and also provides a mechanism for customer engagement and better understanding what is important to them and their integrity programs. This proactive approach relies on accurate infield data from the operators and collaboration between both parties to establish an environment that drives improvement.

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