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Pipeline Technology Journal

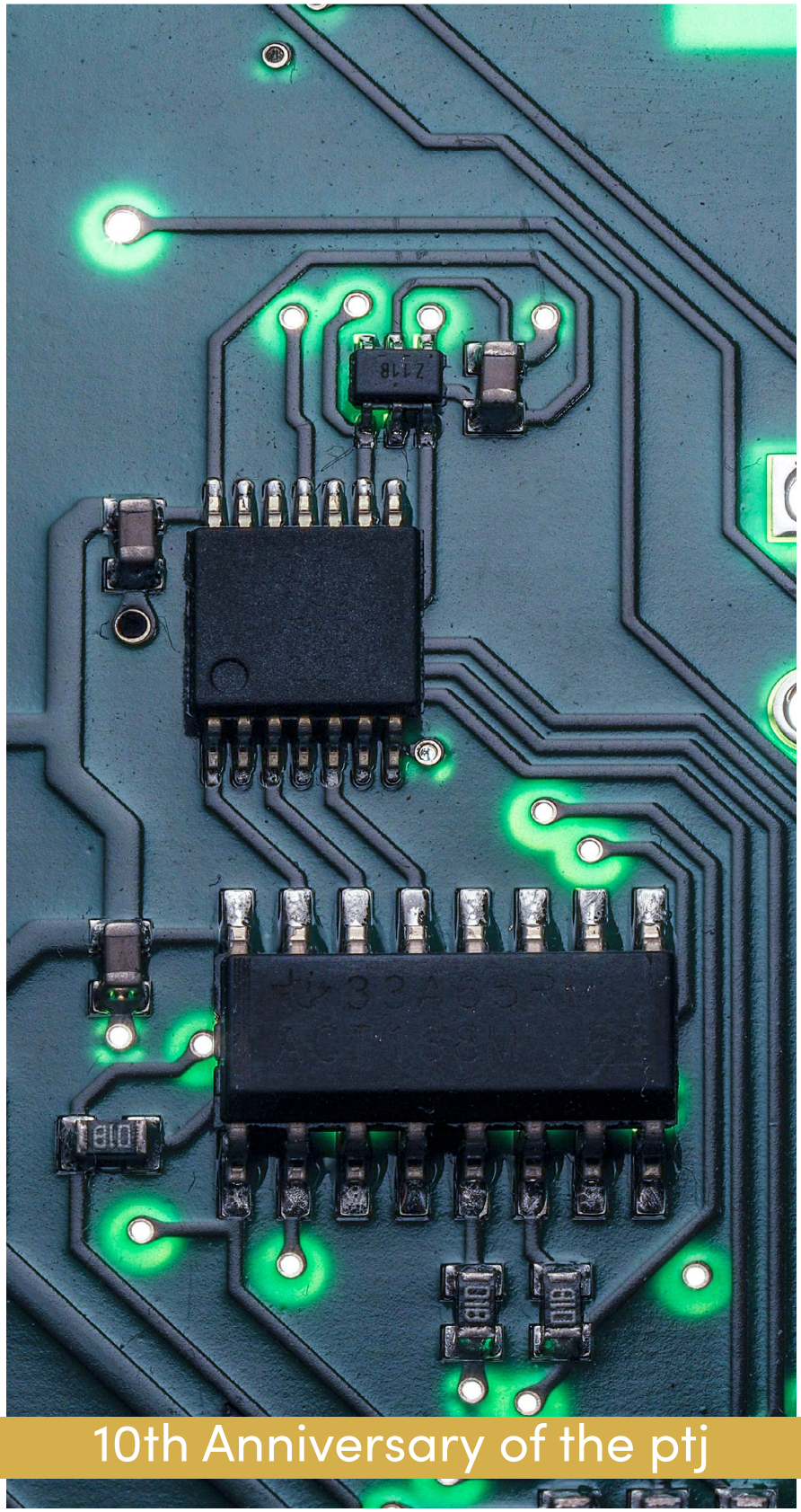
Data Science & Artificial Intelligence

Toward AI Data-Driven Pipeline Monitoring Systems

Pipeline joint identification using neural networks

Enhancing External Corrosion Direct Assessment With Machine Learning

Mastering the Match: A Comprehensive Validation of Run Comparison Software Using Synthetic Data



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Data Science & Artificial Intelligence

Jed Ludlow
Chief Engineer - Global Pipeline Integrity

T.D.Williamson

W. Edwards Deming, a prominent statistician and consultant in the field of quality management during the latter half of the twentieth century, asserted that every corporation should have a skilled statistician reporting to the senior leadership so that critical decisions could be based on sound statistical evidence. The rise of data science as a discipline over the last couple of decades has demonstrated that Deming was at least partially correct—that decisions should be based on sound statistical analysis of data. However, we've learned that it's probably more valuable to instill a little bit of the statistician into everyone rather than rely on a single individual for all the statistical expertise. What has made this shift possible? The tools of applied data science—statistics, machine learning, and artificial intelligence—have become more accessible and available over time, making it much easier for people without a specialized statistical background to reason about data and to build powerful analytical and predictive models.

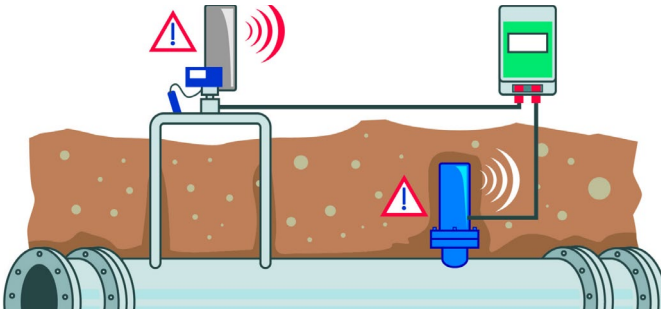
We will see in this issue of the Pipeline Technology Journal how the tools of data science, applied by engineers and scientists, are permeating the pipeline integrity management space to advance the state of the art in inline inspection, integrity assessment, and monitoring. It is exciting to see the tools of data science in the hands of those closest to the critical problems, bringing all their deep expertise in pipeline integrity to the table. Having subject matter experts so close to the efforts raises the likelihood that we are working on the problems that are worth addressing and that will bring lasting value to the pipeline industry.

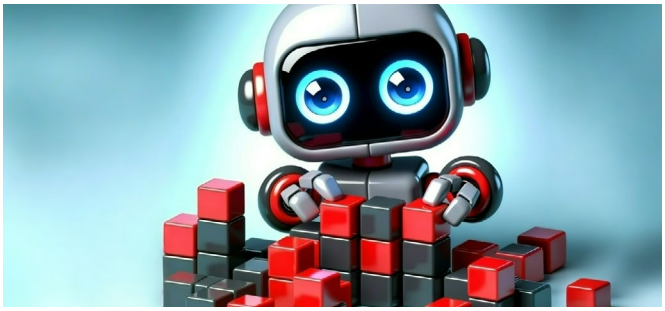
Sincerely,

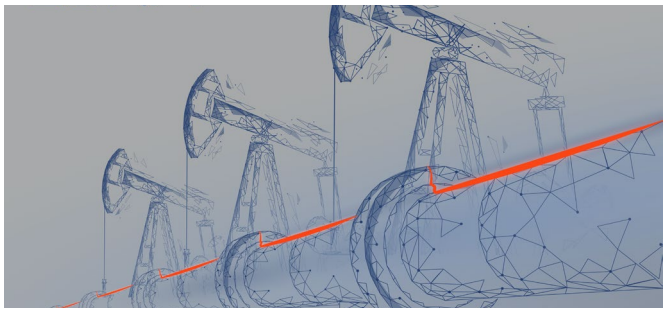
Jed Ludlow
Chief Engineer - Global Pipeline Integrity
T.D.Williamson

This Issue's

COMPLETE CONTENT







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ptc 2024: Shaping the Future of Pipelines on a Global Stage in Berlin

The Pipeline Technology Conference (ptc), Europe's premier event for pipeline industry professionals, is set to return to Berlin from April 8-11, 2024. This much-anticipated conference and exhibition will once again serve as the epicenter of knowledge exchange, innovation, and collaboration for the global pipeline community.

The 19th Pipeline Technology Conference promises an enriching experience for all attendees, with an extensive program encompassing a diverse range of activities. Delegates can look forward to a lineup of 1-day training courses, illuminating panel discussions, in-depth technical sessions, interactive operator round-tables, culminating award ceremonies, and engaging social events.

The pipeline industry is currently navigating a dynamic landscape fraught with an array of unique political, economic and technical challenges across different continents, including Europe, North America, Latin America, Asia, and Africa. Against this backdrop, ptc 2024 will provide a vital platform for the international pipeline community to share invaluable experiences, technical advancements, and lessons learned.

"The Pipeline Technology Conference is much more than an annual gathering. It is an opportunity for the industry elite – pipeline operators, industry leaders, experts, and young talent – to come together and shape the future of the industry," said Dennis Fandrich, Member of the Management Board of the organizing EITEP Institute and Chair of the Pipeline Technology Conference. "We will delve deep into political challenges, explore cutting-edge technological developments, and present real-world case studies that demonstrate our commitment to a net-zero emissions future in Germany, Europe and the rest of the world."

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www.pipeline-journal.net/news/ptc-2024-shaping-future-pipelines-global-stage-berlin

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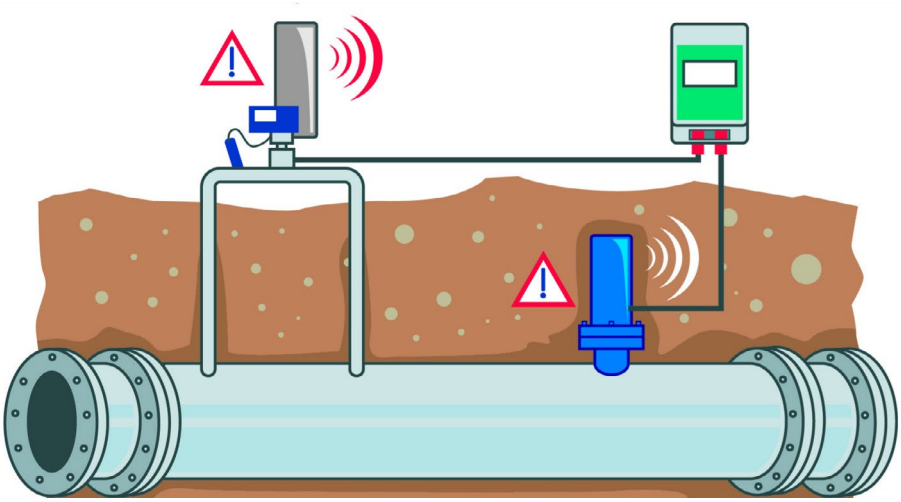

Toward AI Data-Driven Pipeline Monitoring Systems

M. BIAGINI, A. P. GOMES, F. CHIAPPA > ENIVIBES

Abstract

This work focuses on the application of artificial intelligence methods to enhance pipeline monitoring systems, specifically Third-Party Interference (TPI) and leak detection. A critical aspect of pipeline monitoring revolves around determining the operational state of the pipeline. This is paramount because the processing algorithms are intricately linked to this information.

Traditionally, the pipeline's state has been determined through ad-hoc systems known for their robustness and reliability, despite occasional downtime and delays. However, these limitations may occasionally lead the monitoring systems to resort to less reliable algorithms, resulting in false alarms.

This innovative approach incorporates machine learning and deep learning techniques to create a data-driven system, significantly improving overall system performance in terms of both reliability and robustness. This approach enables us to extract valuable features from the data, constructing a data-driven model capable of accurately detecting the true state of the pipeline with minimal error rates and zero delays.

1. Introduction

In an era where energy resources are of paramount significance, the safety and security of pipeline operations are critical not only for operational excellence but also from an environmental perspective. The installation of robust leak and TPI detection systems plays a pivotal role in safeguarding these interests. Beyond operational efficiency, detection systems are integral to the protection of the environment, ensuring prompt response and mitigation in the event of a breach.

Vibroacoustic Technology is an efficient and reliable monitoring tool, detecting leaks and precursor events like excavations through micro-vibrations, pressure, and sound. With the installation of vibroacoustic sensor blocks every few kilometers, this technology enables the identification and differentiation of leakages and TPI incidents. Engineered for efficiency, these sensor blocks are low bandwidth and power consumption. They capture vibroacoustic data created by leakages or TPI activities occurring along the pipeline. In a matter of minutes following a leakage or TPI event, the VT promptly emits an alarm, precisely pinpointing the event's location.

The focus of this paper is the transformative potential of artificial intelligence (AI) methods in elevating the capabilities of the Vibroacoustic Technology in pipeline monitoring systems, with a specific emphasis on addressing challenges related to TPI and leak detection. One of the critical factors in the realm of pipeline monitoring is the accurate determination of the operational state of the pipeline. Traditionally, this determination has relied upon robust yet occasionally prone-to-downtime ad-hoc systems known for their reliability: SCADA and DCS.

This research introduces an innovative approach that connects the power of machine learning and deep learning techniques to establish a data-driven system to determine the operational state of a pipeline. This approach marks a significant departure from traditional methods, promising a substantial enhancement in the overall performance of pipeline monitoring systems in terms of both reliability and robustness with minimal error rates and zero delays.

2. Vibroacoustic Pipeline Monitoring System

2.1 Understand the system

Vibroacoustic Technology comprises a sophisticated system that integrates a multipoint array of vibroacoustic sensors strategically positioned along a pipeline, a telecommunications infrastructure for seamless data transfer, and a centralized processing server. In particular, the sensor arrays are dedicated to capturing the entire elastic-dynamic wave field, providing comprehensive insights into the physical phenomena underlying elastic perturbations.

In this study, all datasets, experiments, and subsequent analyses were conducted within the framework of the vibroacoustic technology platform, developed by Eni [1][2][3][4].

Whenever an event occurs, it generates acoustic and elastic waves from a local source, which then propagate in both directions at the speed characteristic of the medium they traverse. The vibroacoustic sensors meticulously record these waves, while a remote-control unit continuously transmits data segments to the central processing server. This central server assumes responsibility for executing advanced digital processing tasks, including but not limited to nonlinear filtering, real-time noise estimation, event detection, and multi-channel localization (see Figure 1).

When a mechanical disturbance, such as a spillage, impact, or digging operation, interacts with the pipeline, it generates a propagating vibroacoustic wave. These anomalies are detected by the sensors, and their recordings are transmitted to a central processing unit.

The processing system core handles pressure waves in conjunction with micro-vibrations and acoustic data, which allows the system to not only identify but also accurately pinpoint the source of anomalous noise, carrying valuable insights into secondary events. The equipment developed for this purpose exhibits an exceptional level of sensitivity, while the signal processing algorithms are cutting-edge.

From a wave physics perspective, pipelines serve as highly effective waveguide systems. The acoustic pressure field can propagate for kilometers within the fluid when the pressure is at a minimum of 1 bar

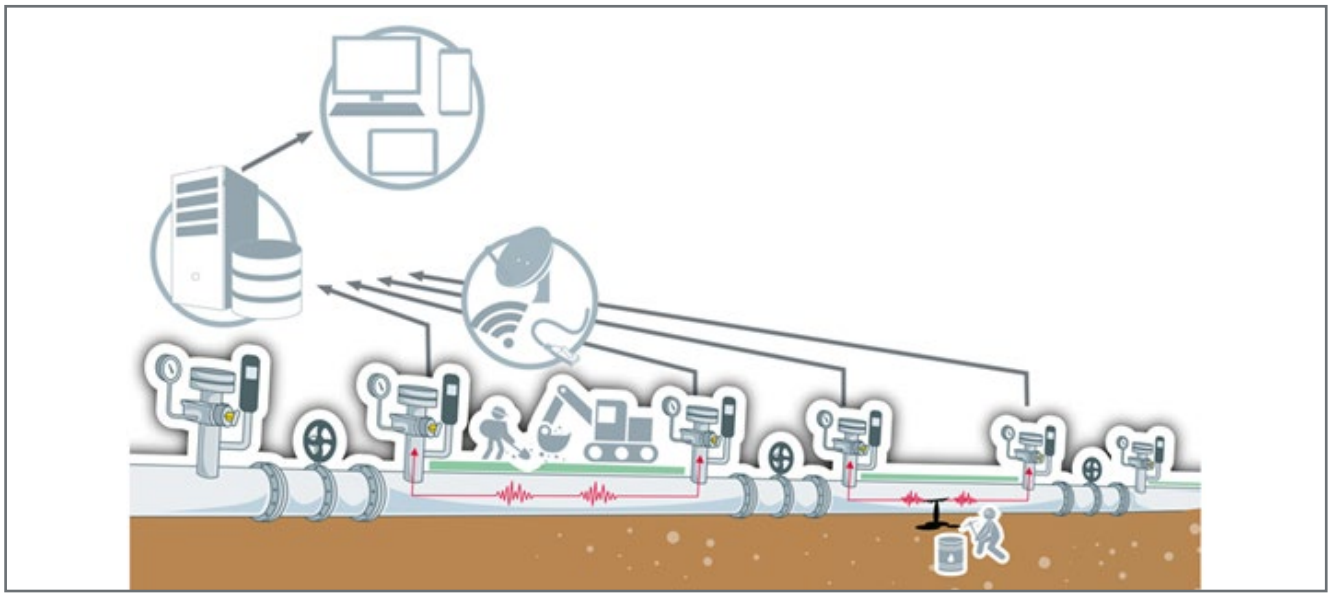

Figure 1: A schematic representation of the Vibroacoustic Technology hardware.

gauge, while vibrations adhere to the elastic-dynamic principles as they traverse the solid shell.

These inherent characteristics endow vibroacoustic technology with a level of detection performance that transcends what a simple pressure-based system can achieve.

Furthermore, the sensor blocks can typically be retrofitted onto existing hydraulic systems without the need for hot tapping, as depicted in Figure 2. Notably, the sensor blocks can also be buried and submersed up to 10m of water level. Also, sensors in direct contact with the fluid are ATEX certified (Ex i) and can function even with mixtures containing H_2S.

The on-field devices have a power requirement of less than 20W and can be powered by various means, such as solar panels, fuel cells, or direct mains connection. Notably, one of the most intriguing aspects of Vibroacoustic Technology is its ability to run for extended periods on a 12V battery, a feature of significant practical value for pilot projects and demonstrations. This capability was leveraged to create a portable version of the entire system.

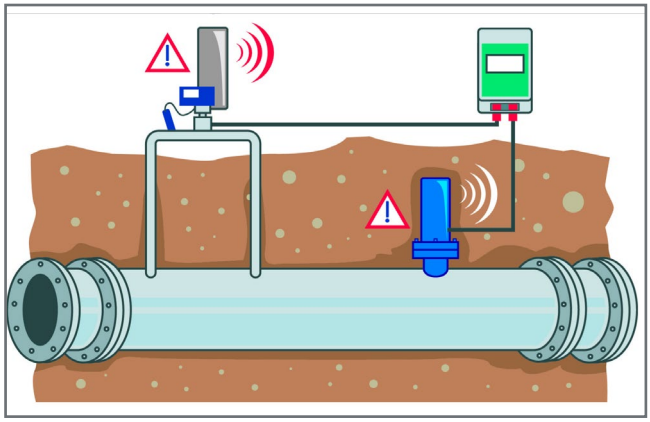

Figure 2 Vibroacoustic sensor units: Standard Sensor (upper left, gray) and Shallow Water Sensor (bottom right, blue). Acquisition Station (top right, green).

Data collected by the field acquisition units are transmitted in real-time to the central processing server. For comprehensive coverage, the network data transfer utilizes available communication channels, including LAN, Wi-Fi, ADSL, UMTS, Satellite, while consuming minimal bandwidth.

2.2 Traditional Approach to status determination

Accurate and timely information about the pipeline's state is essential for ensuring its efficient and safe operation.

Traditionally, the pipeline's condition has been assessed using ad-hoc systems (such as SCADA or DCS) known for their robustness and reliability. These legacy systems, often based on well-established engineering principles, have served as a strong foundation for pipeline monitoring. They offer a tried-and-true approach that has been reliable in various industrial settings, including oil and gas industry.

However, these systems are not immune to delays

and downtime. One notable limitation is the occasional downtime and delays experienced by these traditional systems. Instances where data collection or sensor calibration is disrupted due to maintenance or technical malfunctions can compromise their ability to provide real-time updates on the pipeline's operational status.

These disruptions can be particularly concerning in monitoring, where a timely response is fundamental to avoid generating false alarms and to select the most appropriate processing modality.

3. Novel Approach: toward data-driven system

3.1 The Machine Learning Paradigm

The advancement of technology, particularly in the field of data science and machine learning, offers a promising solution to these challenges. Modern pipeline monitoring systems can harness the power of advanced algorithms and predictive analytics to enhance the reliability and accuracy of operational state determinations.

These intelligent systems can adapt to dynamic conditions and evolving data patterns, reducing false alarms and improving the overall responsiveness of monitoring. Additionally, the integration of sensor networks, data fusion techniques, and real-time data analytics provides a comprehensive and continuous view of the pipeline's operational state. Machine learning models can be trained to detect even subtle deviations in the data, facilitating early anomaly detection and any type of change in the data.

By doing so, they help industries move from a reactive approach to a proactive one, mitigating risks and optimizing resource allocation. In summary, while traditional pipeline monitoring systems have served as pillars of reliability, they are not without their limitations, particularly in terms of occasional downtime, that in monitoring system led to false alarms. Embracing modern technological advancements, including data-driven approaches and machine learning, promises to address these limitations, ushering in a new era of pipeline monitoring that is more adaptive, accurate, and proactive. This evolution aligns with the growing demand for increased efficiency, safety, and sustainability across various industries, making it a pivotal step forward in the management of critical infrastructure.

3.2 Introduction of the classification problem

The classification problem is a central and pervasive concept both in machine learning and data analysis, serving as the foundation for numerous applications across a myriad of disciplines. At its core, this problem involves the task of sorting and categorizing data into distinct groups or classes, thereby enabling automated decision-making based on the characteristics of the data. It represents one of the fundamental supervised learning tasks, where models are trained to discern patterns within the data and predict the appropriate class or category to which each data point belongs.

3.3 Our approach

In this paper, our approach aims to estimate real-time status to address the issues outlined in the previous section. We achieve this by leveraging deep learning techniques based on fully connected neural networks. These networks have been trained using a multitude of features extracted from pressure data obtained from sensors located at the ends of the pipeline. Our system utilizes the model derived from the neural network to provide highly efficient, data-driven status estimation, which proves to be more robust against delays and downtime.

Furthermore, accurate status identification enables us to select the most efficient processing algorithms, thereby enhancing the effectiveness of the monitoring system. Specifically, we have identified four distinct states, as detailed in Table 1, along with the corresponding labels employed for neural network training.

Pipeline Status	Label
Sealed	0
Transferring	1
Transition phase (from Sealed to Transferring)	2
Transition phase (from Transferring to Sealed)	3

Table 1: Pipeline status and labelling

4. Results

In this section we present the classification outcomes obtained from a real pipeline monitoring system deployed in Italy. Figure 3 shows the decision surfaces created using selected features from the entire dataset.

In Table 2, the confusion matrix shows how the error is distributed among the four classes. Specifically, the system achieves a remarkable 99% efficiency on both the training and testing datasets, underscoring its robust and effective status determination capabilities.

A noteworthy observation refers to the prediction error during transition phases, as evident from the table, the majority of errors are associated with these two classes (due to the non-stationary condition). However, in this scenario, the error is negligible because both transition time phases utilize the same processing algorithm.

Moreover, in Figure 4, the predicted status is depicted alongside the pressure, illustrating the robustness of the status prediction concerning the pressure measured by sensors.

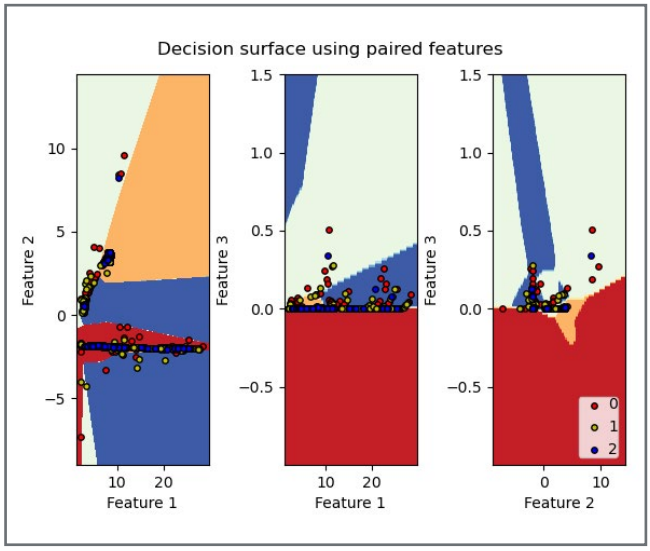

Figure 3: Decision Surfaces

Real Status \ Pipeline Predicted Status	0	1	2	3
0	2651	0	0	0
1	0	1069	0	0
2	3	0	90	5
3	23	4	18	53

Table 2: Confusion Matrix

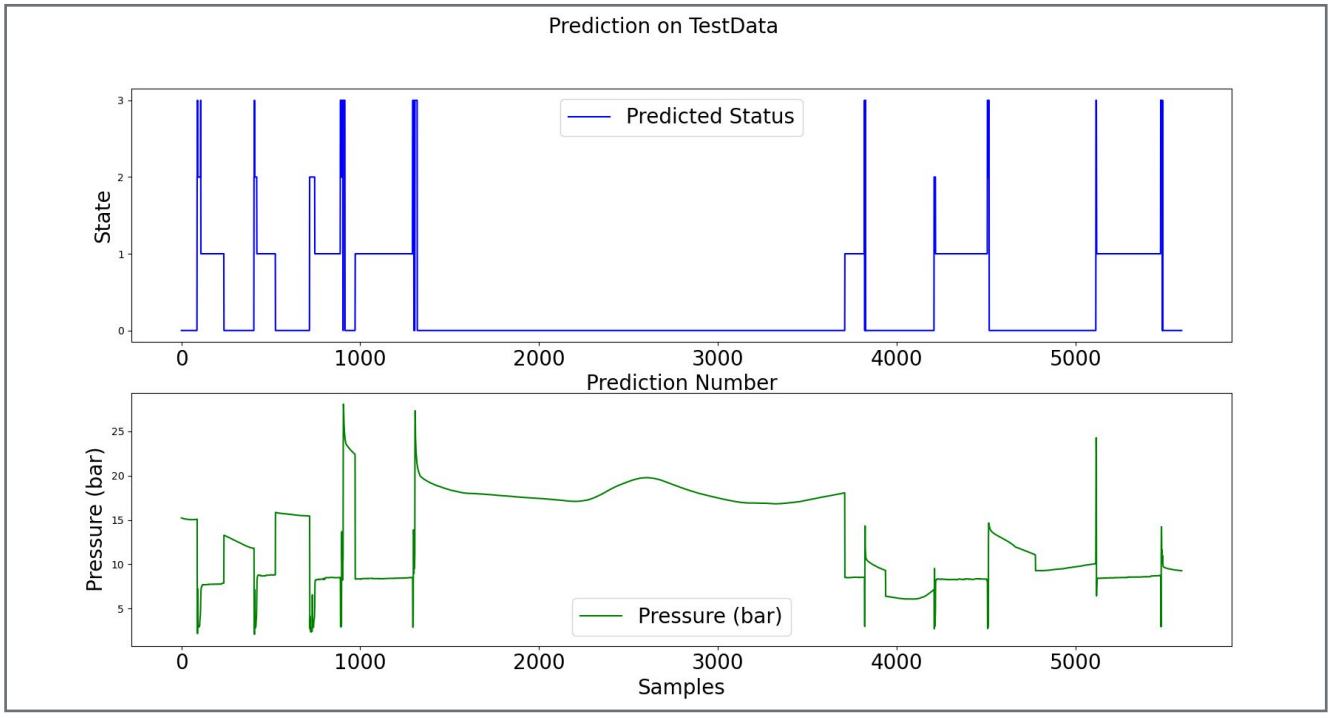

Figure 4: Predicted status vs measured pressure

5. Final Remarks and Conclusion

Vibroacoustic Technology is an efficient and cost-effective method for real-time spotting of leakages and TPI incidents. The system's adaptability in design, retrofit convenience, extensive event detection capabilities, and support for pipeline operations with minimal sensors showcase its prowess. This adaptability extends to challenging environmental and remote scenarios, further solidifying its installation viability.

The innovative data-driven approach employed in this system has yielded remarkable results, achieving an outstanding accuracy rate of up to 99%. This exceptional level of precision allows us to attain a very reliable and robust system. One of the key advantages of this data-driven approach is its resilience in the face of challenges that traditional systems might encounter. By relying on data for decision-making, this solution effectively minimizes vulnerabilities to delays and downtime. This is a significant step forward in ensuring uninterrupted and consistent system performance.

The robustness of this approach can be attributed to its ability to adapt and learn from the data it processes. In the face of changing conditions or unforeseen events, the system can continuously improve its performance, making it highly reliable in dynamic and real-world scenarios. As a result, it can provide a consistent and dependable service, even in situations where traditional, rule-based systems might falter.

In conclusion, the data-driven approach presented in this solution, with its exceptional accuracy and resilience to delays or downtime, represents a groundbreaking shift in the world of monitoring systems.

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Pipeline Joint Identification using Neural Networks

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Abstract

Conventional inline inspection (ILI) tools use odometer wheels to determine the location of identified defects. On top of that, above ground markers (AGMs) are used to confirm and potentially correct for odometer wheel slippage. Free-floating unconventional ILI tools use information from a variety of sensors to accurately locate defects. Accurately identifying joints is a prerequisite for localization and automatic identification of the joints is key for a cost-effective inspection.

This paper focuses on automating the joint identification process with a neural network. This article will describe deep learning strategies for discrete feature identification and segmentation in time series data, how those strategies are increasing data processing efficiency, current accuracy and limitations, and normalization strategies for data from multiple sensors.

1. Introduction

In 2016, a significant pipeline failure in North America led to the uncontrolled release of 2,000 metric tons of hydrocarbons [1]. Since the 1980s, magnetic flux leakage (MFL) and ultrasonic devices have served as the primary tools for pipeline integrity management. However, the existence of tight bends, non-circular valves, diameter changes, or unknown geometries renders approximately 70% of pre-ILI-era US gas lines "unpiggable" [2]. A survey from 2012 indicated that 40% of gas pipelines in North America fall into this category [3]. Consequently, novel technologies have emerged since the early 2000s to address the challenges associated with inspecting unpiggable lines [4,5].

Accurate defect localization within pipelines has always presented a challenge. Traditional ILI tools employ odometer wheels, but issues like slippage, especially in lines with heavy deposits or rough surfaces, persist [6]. To enhance accuracy, external above ground markers (AGMs) are used, available in magnetic, acoustic, or geophone array varieties [7,8,9]. However, their cost and limited accuracy in urban areas, depending on pipeline depth, pose challenges. Multisensor free-floating devices offer an alternative approach to address the localization problem, accompanied by their unique set of strengths and challenges. Weld identification based on magnetometer data plays a crucial role in mapping measurement time to measurement distance [10]. The automation of this critical bottleneck significantly bolsters the scalability of multisensor free-floating devices. Here we present a neural network (NN) which can successfully automate the detection of pipe welds in steel pipes from residual magnetometer data with near human level performance.

2. ONE DIMENSIONAL SEGMENTATION WITH UNET-STYLE NETWORK

The morphology of joints, as detected through residual magnetometry, varies considerably. Some pipeline joints exhibit a straightforward peak search, while others manifest as subtle oscillation frequency variations. Some are so inconspicuous that it is necessary to consider the average joint spacing in the surrounding area to determine which magnetic features are joints. Given the lack of precise and articulate attributes for joint identification amenable to imperative programming, a neural network (NN) emerges as the most promising solution. This paper conceptualizes joint detection as a 1D segmentation problem, with labels applied to individual data points (either joint or non-joint). A neural network is designed to classify each data point, taking four magnetic vectors as inputs (m_x, m_y, m_z, and m_t where $m_t = (m_x^2 + m_y^2 + m_z^2)^{0.5}$). The network returns two values, y_1 and y_2, to estimate the likelihood of a joint at each position, represented by a softmax function [see Figure 1].

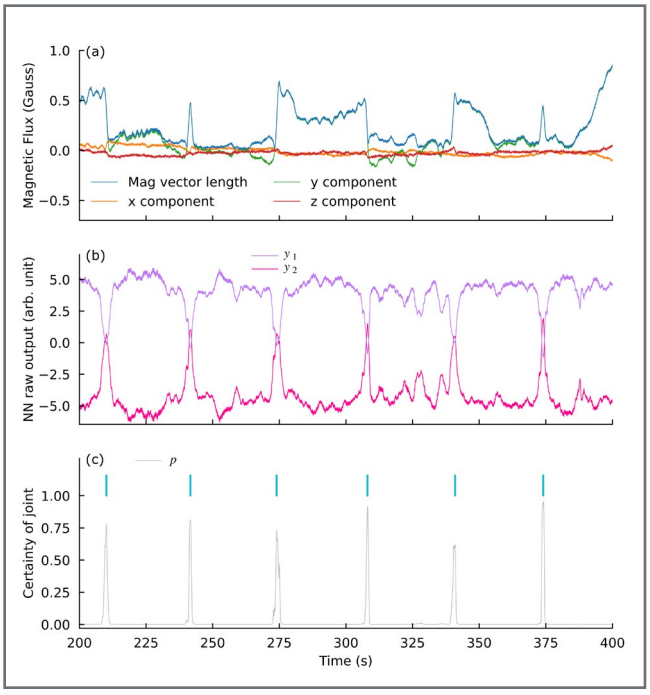

Figure 1: (a) Inputs to the neural network are not normalized due to the magnitude of the values and the absence of a natural normalization reference. (b) The raw output of the neural network is displayed in arbitrary units. (c) The softmax of the neural network output vectors from (b) provides a measure of certainty for each joint detected, with a peak search producing a list of joints (shown in cyan).

3. UTILIZING UNET FOR 1D SEGMENTATION

Since the seminal publication of UNet in 2015 [11], fully convolutional neural networks have become the standard for segmentation tasks, with thousands of variations and applications documented. This application of UNet necessitates some modifications. As we deal with 1D data instead of 2D data, we must increase the receptive fields to account for the greater distance between data points. Furthermore, the precision required for joint identification is lower than that for medical image segmentation, allowing us to use smaller output arrays. Additionally, given our data

source (pipeline magnetics) in contrast to cell micrographs, training data augmentations differ.

Expanding the receptive field to encompass multiple joints allows the neural network to capture context, similar to manual joint identification. This is crucial because what may be considered a joint in one pipeline's magnetic signature might merely be a normal fluctuation in another line. As information flows through the UNet, a broader receptive field is necessary for accurate point classification. The receptive field of a neuron in a convolutional and pooling neural network is determined by the kernel size and stride. By adjusting these parameters, we expanded the receptive field to encompass a wider area, enhancing context capture.

Transpose convolutions were used to reverse the compressions of max pool and convolutional layers. This design choice, combined with input array length divisibility by the encoder layer strides, improved training performance.

3.1 Architecture and receptive fields for 1D data

Figure 2 illustrates the architecture of a fully convolutional UNet for 1D segmentation. Note that the dimensions are not proportional due to changes in tensor length as it progresses through the network. The receptive field of the network has been expanded to encompass multiple joints, enhancing its contextual understanding. Transitioning from 2D to 1D data reduced the total input data by 85% but increased the maximum distance between points by a factor of 90. Increasing the strides and kernel sizes of the convolutional layers was necessary to enable accurate contextualization of magnetometer data.

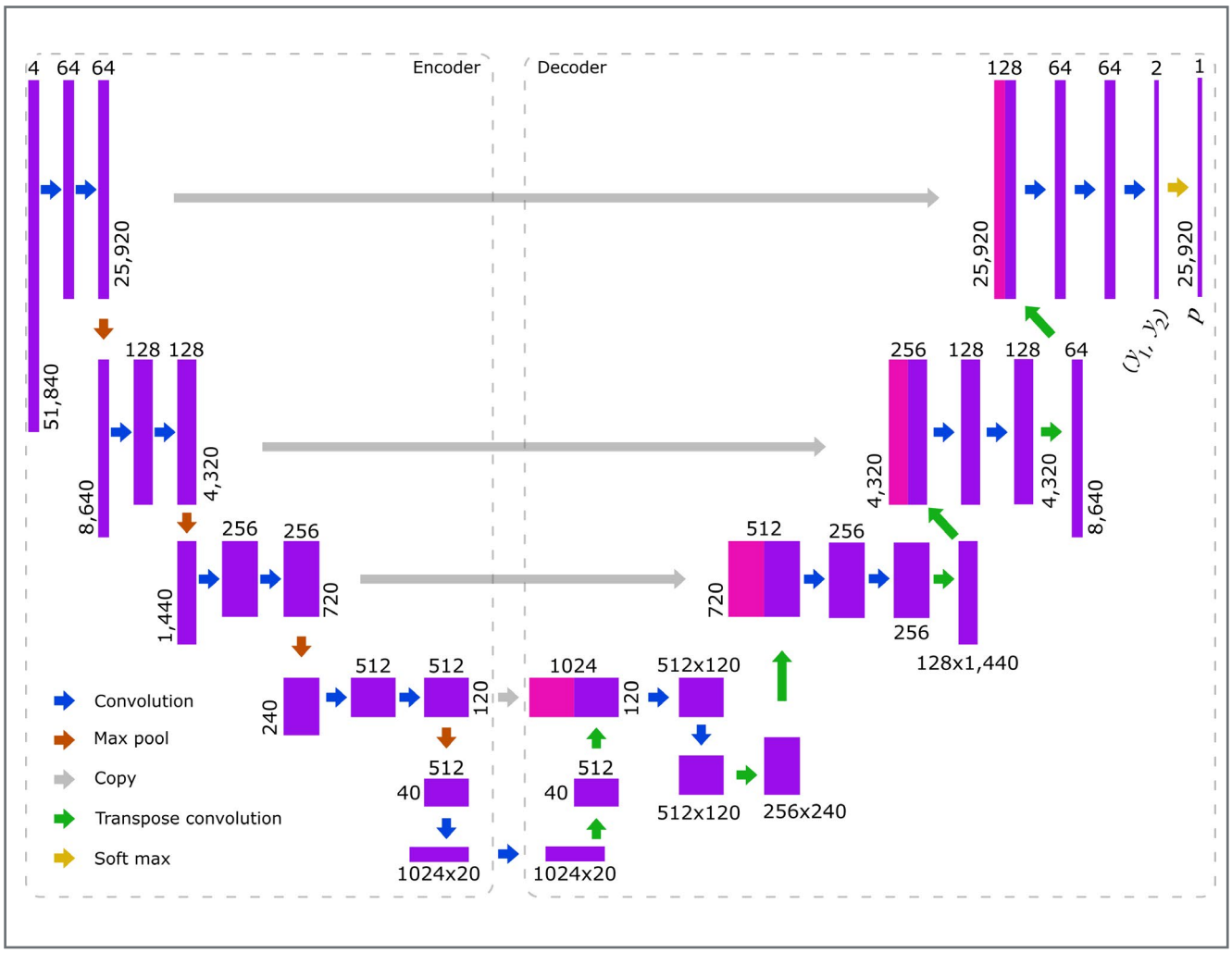

Figure 2: Architecture of fully convolutional UNet for 1D segmentation
Rectangular dimensions are not proportional to length because the length of the tensors changes by a factor of 2,600 as it moves through the network. All convolutional layers have a kernel of 3. On the encoder side of the network, the stride is 2 or 1 for the first or second in each pair, respectively. On the decoder side, the stride is 1 for all convolutional layers. All transpose convolutional layers have a kernel of 3; the stride is 2 or 3 for the first or second in each pair respectively. Max pool layers have a kernel and stride of 3. ReLU activations functions follow each convolutional or transpose convolutional layer.

3.2 DATASET AND AUGMENTATION

The question of how much training data a neural network requires remains a topic of active research [12,13]. Generally, estimates range between 10 and 1000 times the number of parameters in the model. Our neural network comprises 12.6 million parameters and approximately 100,000 joint examples, which, given the need for multiple joints per sample, are not fully independent. To address this, we employed various data augmentations, resulting in 3 million training samples. Remarkably, our networks exhibited convergence and generalization with two orders of magnitude less data than typically expected for models of this size. We expect further improvements as our data library grows.

To generate an augmented data sample

- Select random survey
- Select random subset of survey 37.5k to 70k data points long
- Resample by linear interpolation to 50k data points (stretch or compress in x axis)
- Multiply each component by random scaler value from 0.7 to 1.33 (stretch or compress in y axis)
- With 50% probability, reverse the sample (mirror in x axis)
- With 50% probability, multiply x, y, and z components by -1 (mirror in y axis)
- Randomly reorder x, y, z components. Because measurements are taken free-floating, the orientation of the sensor is random so random reordering of components is a valid augmentation strategy.

3.3 LOSS FUNCTIONS AND GROUND TRUTH

The training data's y values represent discrete points, whereas our output is a segmentation output. To create suitable ground truth for a segmentation algorithm, we define "joint" within a 50-data-point window and "not joint" elsewhere. Our network is trained using a standard cross-entropy loss function without any differential weighting applied to data points. Unlike the original UNet, which emphasized edge detection, our application prioritizes learning class distinctions at data point centers rather than precise segmentation edge identification. Thus, this network was trained using a standard cross-entropy loss function with uniform weighting across data points.

4. MULTISENSOR DATA APPROACH

Although joint signatures are visible in the magnetometer data in >95% of pipelines, when affixed to the back of a cleaning pig the combination of accelerometer, gyroscope, and magnetometer data allows for cross validation among different sensors and higher accuracy. Utilizing accelerometer, gyroscope, and magnetometry data when attached to a cleaning pig proves more effective in joint detection than relying on a single sensor. Joint signatures may not be discernible in one or more of these sensors due to factors like a poorly fitting pig or incomplete weld penetration of the pipe wall. To ensure correct integration into our neural network, we normalize gyroscopic and acceleration data by the maximum value in each 200-second window.

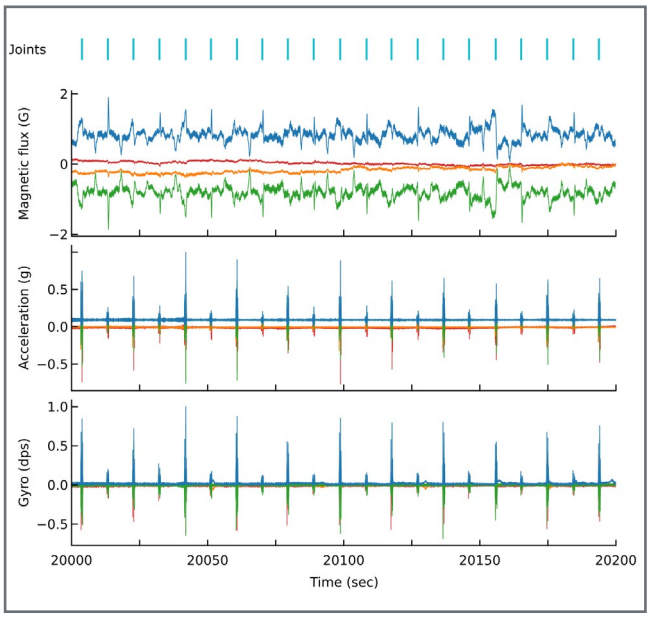

Figure 3: When the sensor is run on the back of a cleaning pig, joints appear in the magnetometer, gyroscope, and accelerometer data. The network accepts 12 input channels (x, y, z, and total for each of the three sensors; x: red, y: green, z: orange, and total: blue). The four acceleration or gyroscope channels are normalized by the max of the total acceleration or gyroscope signal, respectively.

For the pigged-only neural networks, we can randomly switch the x and z axes, but the y axis is fixed in the field data (parallel to the direction of travel within the pipe). Other data augmentations are valid but must be applied equally across all sensors (mirrored the same, stretched in x the same, etc).

5. RESULTS AND FUTURE WORK

We have explored a range of neural networks with varying training cycles (50-150k), learning rates (0.01 to 0.3), and minibatch sizes (20-50). In validation datasets, these networks demonstrated false positive rates of 1-2% and false negative rates of 3-5%, approaching human-level performance (0.1 to 2% discrepancy between manual labelers). Even with training networks with 10 million parameters on less than 100,000 examples before augmentation, they have shown considerable potential. We anticipate further improvements as our data library expands, with the potential to surpass human-level performance.

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Enhancing External Corrosion Direct Assessment With Machine Learning

L. BARTON > ROSEN

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).

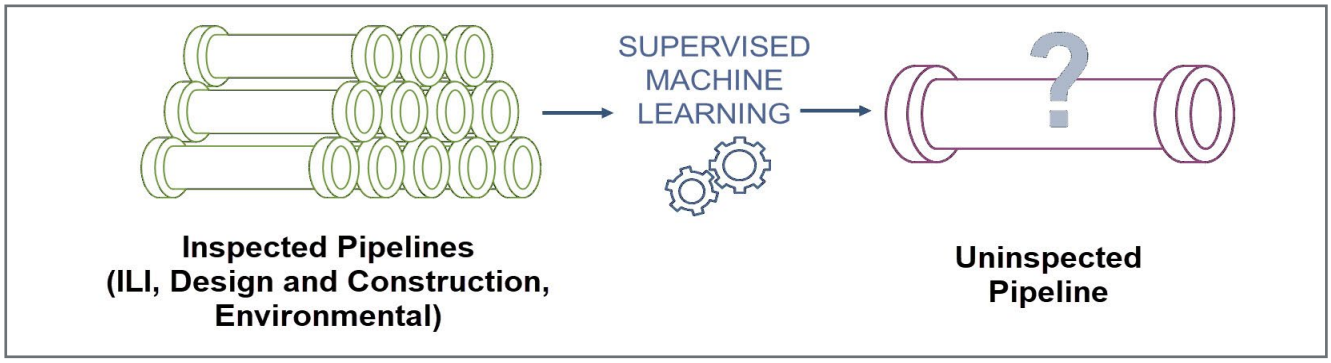

Figure 1: The fundamentals of Virtual-ILI

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 m²) 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.

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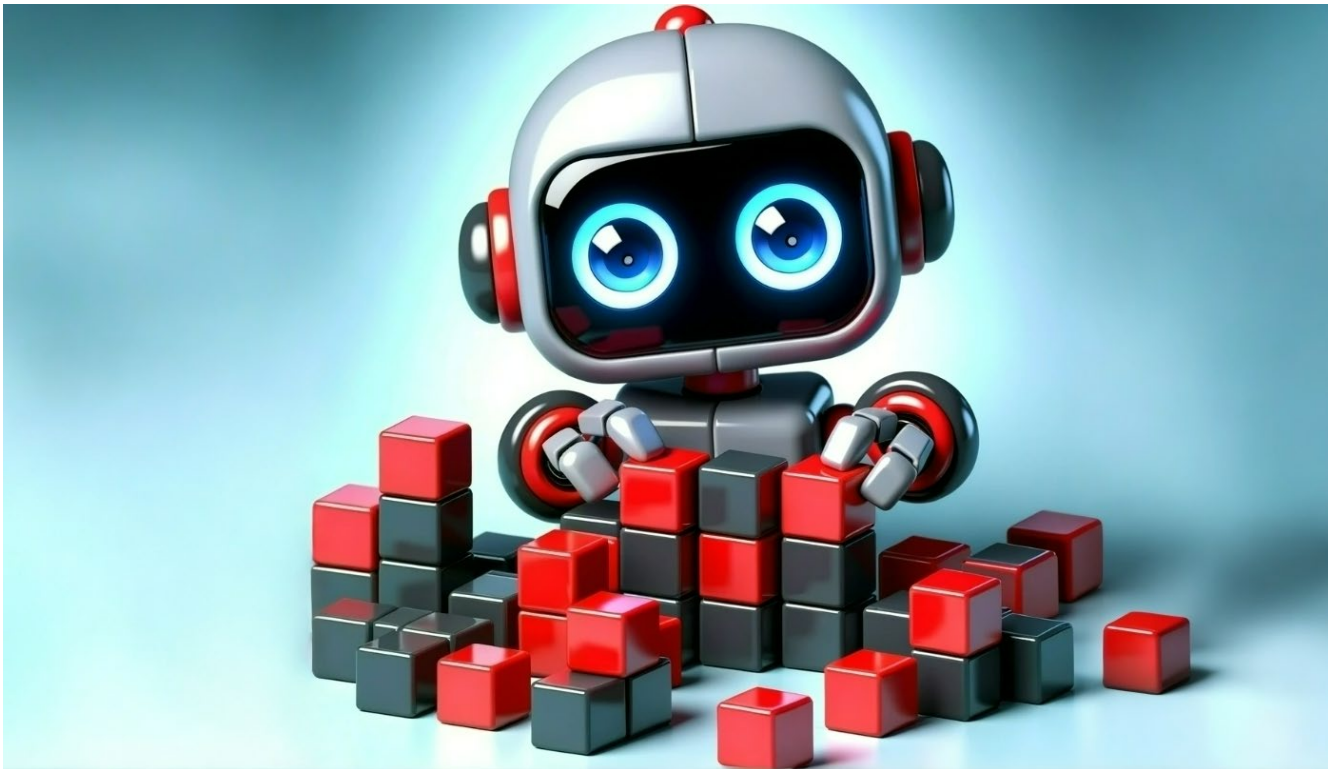

Mastering the Match: A Comprehensive Validation of Run Comparison Software Using Synthetic Data

S. BOKHANKEVICH > T.D. WILLIAMSON

Abstract

This study rigorously validates run comparison (RC) software, essential for accurate corrosion growth rate assessments in pipelines, using an extensive synthetic dataset and an experimental K-nearest neighbours-based algorithm across 2,000 diverse spools. Detailed within the paper are the synthetic data generation, in-line inspection (ILI) run simulations, and algorithm validation processes, facilitating a nuanced understanding of the algorithm's performance under varying conditions.

Results highlight the significant impact of anomaly distribution on RC accuracy, with noticeable performance declines as anomaly counts increase, especially in scenarios with circumferentially concentrated anomalies. However, the algorithm maintains commendable accuracy and robust performance across various tests.

This research not only sheds light on critical factors affecting RC performance but also sets a robust framework for future evaluations and underscores the need for representativeness in synthetic datasets, guiding enhancements in RC algorithms. Future directions include improving algorithmic resilience in high-density anomaly conditions, refining validation frameworks, and diversifying matching scenarios.

1. Introduction

After conducting in-line inspection (ILI), distributions of anomaly depth changes are interpreted to estimate corrosion growth rates (CGR). These distributions are primarily derived from run comparison (RC). This comparison can be executed through signal matching or "box matching" when at least one set of ILI results is tabulated. In this context, a "box" represents an anomaly abstraction, visualized as a rectangle. The rectangle's length and width correspond to the anomaly's dimensions.

However, these distributions can have inherent errors. Some errors stem from uncertainties in the ILI model, while others arise from issues related to ILI repeatability [1]. When RC performance is suboptimal and cannot be sufficiently rectified, engineers might be compelled to adopt more conservative practices. One such method involves selecting a smaller sample of deep anomalies and manually matching them. This strategy can lead to substantial overestimations of CGR. As such, ensuring the robustness of RC software is of paramount importance. “Box matching” can be addressed using various approaches. The initial publication extensively discussed the adaptation of a simple machine learning (ML) method for this purpose [2]. Although numerous configurations were explored, the evaluation encompassed only two pipeline spools, totalling 163 relevant data points (both matched anomalies and those left unmatched). Prior to potential operational deployment of the model, there exists a pressing requirement to assess it more extensively using a more comprehensive dataset. This paper delves into an efficient evaluation technique employing synthetic data and unveils the performance outcomes of the experimental RC method.

2. Background

Prior to model evaluation, it is important to position the box matching task within a broader ML framework and recap the main working principles of the RC algorithm being examined.

2.1 Fundamental Dichotomies in Machine Learning Models

While there are numerous ML methods tailored for a diverse range of tasks, understanding the ML landscape can provide clarity on the most suitable approach for a specific challenge at hand. Multiple ML model dichotomies can be discerned [3]:

Supervised vs. Unsupervised Learning:

- Supervised Learning: In supervised learning, models are trained using labelled data. This means that the training dataset includes both the input data and the corresponding correct output (i.e., label: either continuous or discreate variable). The goal of a supervised learning algorithm is to learn a mapping from inputs to outputs and make predictions on new, unseen, and unlabelled data. Common applications include image classification, spam detection, and price prediction.

- Unsupervised Learning: Contrary to supervised learning, unsupervised learning involves training models using datasets without labels. The aim here is to identify patterns or relationships in the data. Clustering and association are two types of problems solved by unsupervised learning. Examples include customer segmentation and anomaly detection in internet traffic.

Regression vs. Classification:

- Regression: Regression algorithms predict a continuous output. In simpler terms, they are used when the output or the dependent variable is a real or continuous value, such as predicting house prices, temperature, or sales amounts.

- Classification: Classification algorithms, on the other hand, are used when the output or the dependent variable is categorical or discrete. This means that they are employed to classify data into predefined classes or labels. Examples include email spam detection (spam or not spam), disease diagnosis, or image categorization.

Model-based vs. Instance-based Learning:

- Model-based Learning: In this approach, a model is built from the training data, and then this model is used to make predictions. Once the model is built, the training data is no longer needed to make new predictions. Examples of model-based

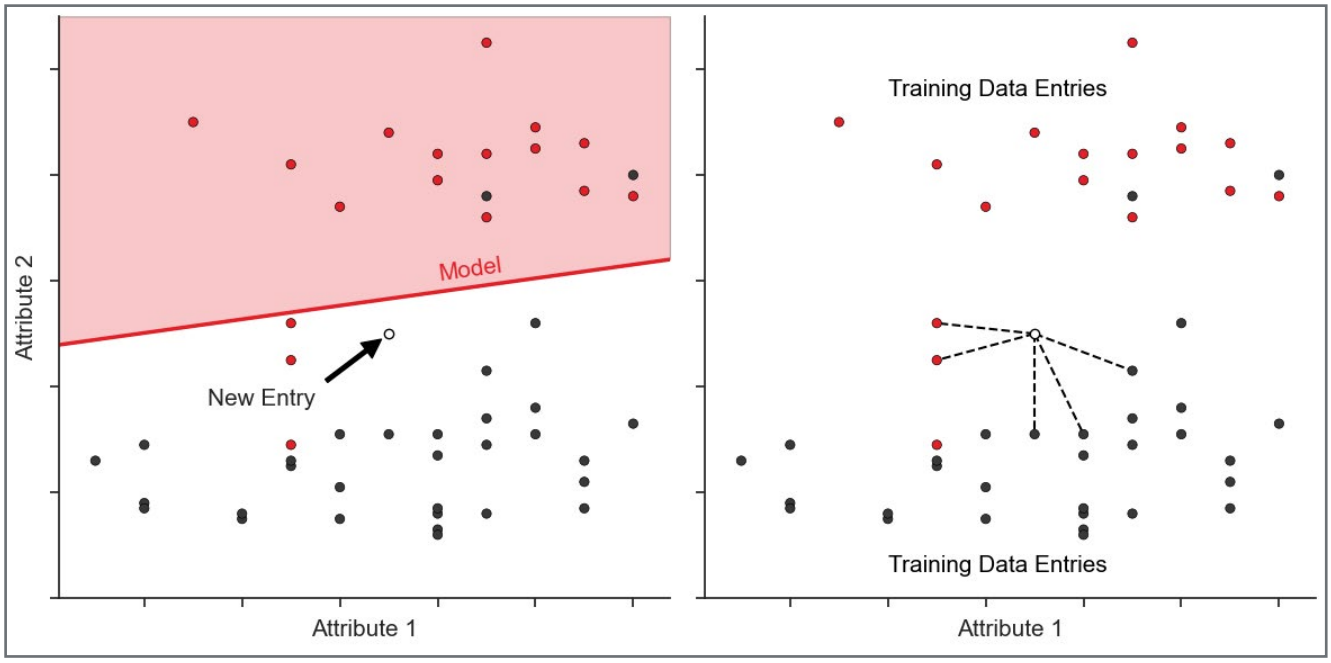

Figure 1: Mode-based and instance-based learning [3]

learning methods include linear regression, decision trees, and neural networks. As depicted in Figure 1's left subplot, a linear model classifies new entries above the line as belonging to the red (top) class.

- Instance-based Learning: Instead of building a model, instance-based (or memory-based) learning methods store the training data and use this data to make predictions. The idea is to find similarities between the stored data and the new data to predict the output. K-nearest neighbours (KNN) is a classic example of instance-based learning, where the algorithm looks for the 'k' training examples that are closest to a new entry and returns the most common output value among them. The right subplot of Figure 1 demonstrates the five nearest neighbours to a new entry, which is classified as black, reflecting the majority class among these neighbours.

2.2 Application of Machine Learning for ILI Run Comparison

The "Box matching" problem can be framed as a classification task using supervised ML. Anomalies from the current inspection are treated as known records, while those from the previous ILI results are viewed as data entries needing classification. Unique anomaly labels, often seen as numbers in pipe tallies, act as classes. For each previously detected anomaly, a corresponding label from the current ILI is predicted. These labels are subsequently used to merge the anomaly lists, making it possible to derive anomaly delta depths.

In contrast to standard supervised ML scenarios, which often have a data set with many labelled entries and few labels available to develop a model, the RC task presents unique challenges:

- The number of unlabelled data entries (boxes from the previous ILI) is roughly the same as the training records (boxes from the current ILI).
- Some boxes from the previous ILI may not have a corresponding anomaly in the current inspection results and should remain unlabelled.
- Each label should be used exactly once (although this requirement might depend on anomaly types being compared).

These challenges make many supervised, model-based ML methodologies less suitable. However, the instance-based KNN algorithm can be effectively tailored for this task. The process for a KNN classifier suited for box matching is as follows [2]:

1. Start with a pipe spool containing anomalies reported in both ILIs.

2. For each previous anomaly, use a similarity measure to find the pool of k' closest current anomalies within defined spacing limits.

3. Choose a previous anomaly and match it with the label of the most similar current anomaly from the appropriate pool.

4. Remove the used label from all pools.

5. Continue with steps 3 and 4 until all previous anomalies have a label or no labels remain in the pools.

In this process, k' and spacing limits are the algorithm hyperparameters, which are predefined settings or configurations that can be adjusted before the spool-wise inference described in the procedure. Previous anomaly selection at step 3 can be done either sequentially starting with the most upstream anomaly and going downstream or based on the similarities computed with the applied distance metric.

Regarding distance metrics, the Minkowski metric is among the most prevalent. Expression (1) conveys the metric's general form, showcasing the distance, d, calculation between D-dimensional feature vectors $\vec{x}_n$ (an unlabelled data entry) and $\vec{x}_i$ (a known entry with a label). Each vector represents an anomaly and its attributes, such as depth and orientation. Dimensionless attributes and attributes with different physical units may be involved in distance computations as long as it leads to better classifier performance. Attributes may require additional pre-processing, such as scaling, before being incorporated into metric calculations. Furthermore, using a set of dimensionless weighs, $\vec{w}$, can bolster the algorithm's by emphasizing the most influential attributes.

$$d(\vec{x}_n, \vec{x}_i) = \sqrt[n]{\sum_{j=1}^{D} \vec{w}^{(j)} \sum_{j=1}^{D} \left| \vec{x}_n^{(j)} - \vec{x}_i^{(j)} \right|^n} \qquad (1)$$

3. Algorithm Validation Framework

As in the validation of any supervised ML model, the two key components of the framework are a labelled data set and a suitable performance metric.

3.1 Datasets

In the context of run comparison, a labelled dataset should comprise numerous anomaly matches, which are either validated by human experts or confirmed accurate through other methods. At least two strategies can be employed to obtain such a dataset:

1. Manually match as many anomalies as feasible across multiple spool pairs.

2. Generate synthetic data.

The first approach, although thorough, is labour-intensive. To achieve a dataset of adequate size, even minor anomalies within selected pipe spools must be paired. It is essential to select spools from various ILI projects to capture diverse anomaly axial and circumferential location distributions. While there is not a definitive size threshold that qualifies a dataset as sufficient, the general principle is that larger datasets yield better results. Ideally, aiming for tens or even hundreds of thousands of anomaly matches would be beneficial, though this would require significant time investment (about 830 hours for 100,000 matches at a rate of two anomaly matches per minute).

This paper is focused on the application of the second strategy: the use of synthetic data. In fact, if a dataset is not readily available, sometimes a synthetic one can be generated. After all, the primary attributes required to estimate similarity between two anomalies are distance from the upstream girth weld and orientation. If the generated data accurately reflect realistic corrosion patterns and ILI tool performance, there is potential to synthesize an unlimited number of matches. This offers versatility in capturing diverse scenarios, including varying distributions, anomaly counts per spool, and discrepancies in two ILI results.

3.2 Application of Synthetic Data

The utilization of synthetic data for validating the RC algorithm encompasses several distinct stages:

1. Generate anomaly and weld listings, ensuring each anomaly is characterized by its true attributes. These attributes should include circumferential and axial locations relative to the nearest upstream weld, as well as the anomaly's dimensions: depth, length, and width. Critically, a unique identifier must be assigned to each generated anomaly.

2. Simulate two ILI runs to produce results that reflect the characteristics of the true anomalies after applying the specified detection and sizing criteria. Within these simulated ILI results:

   a. Some anomalies may be omitted, aligning with the probability of detection (POD).

   b. The dimensions of the remaining anomalies should be adjusted in accordance with the ILI sizing specifications.

   c. Alterations to both circumferential and axial locations of the remaining anomalies should be made by incorporating a constant or variable offset to anomalies in one of the simulated ILI runs.

4. Preserve the unique ID values of the remaining anomalies for subsequent analysis.

5. Proceed with the run comparison. After aligning welds and anomalies, the outcomes of the RC can be thoroughly examined, with anomaly ID values serving as a crucial element for evaluation. The performance metric is elaborated upon in the corresponding section below.

Figure 2 displays 25 synthesized true anomalies, exhibiting uniform distributions in both axial and circumferential locations. This implies a potential occurrence of anomalies at almost any position along the spool. Crucially, these boxes are programmed to avoid overlapping, a feature that distinguishes this synthesis approach from a mere generation of random numbers. Figure 3 and Figure 4 showcase the transformations of these 25 true anomalies following simulations of two ILI runs. The observed absence of anomaly number two in the first ILI run and anomaly number six in the second run is attributed to the application of POD modelling. The uncertainty in axial and circumferential locations is governed by normal distributions, in accordance with the sample specifications provided in appendix A of API 1163 [4], and no additional offsets have been applied. The sizing uncertainty of the ILI tool is also modelled using normal distributions, aligning with the typical specifications for magnetic flux leakage (MFL) ILI for pitting, as defined in the Pipeline Operator Forum (POF) anomaly classification [5].

3.3 RC Performance Metric

Numerous performance metrics are available for evaluating classification algorithms, with sensitivity and precision among them, reflecting the model's ability to correctly label true instances of a specific class [3]. However, considering the unique challenges inherent to box matching (as previously discussed), a variant of accuracy is determined to be the most suitable metric. In the outcomes of run comparison, the alignment of anomalies can result in the following instances:

- Correct matches: Instances where both anomalies have the same ID are deemed correct.
- Incorrect matches: Instances where the paired anomalies have differing IDs are considered erroneous.
- Correct non-matches: Situations where an anomaly is only present in one ILI run and is accurately left without a match.
- Incorrect non-matches: Occurrences where an anomaly is present in both ILI runs but is mistakenly left unmatched.

Non-matches present a complex scenario as their quantity is contingent on the reference run. To explain, consider a pipe spool subjected to two ILI runs. The first run finds 130 anomalies (N_1), and the second ILI finds 150 anomalies (N_2). Assuming 100 matches are made, with 80 being correct (CM), the first run would have 30 non-matched anomalies. If 17 of those were undetected in the second ILI, these would be 17 correct non-matches (CNM_1), and 13 incorrect ones relative to the first run. Conversely, if 27 of the 50 non-matched anomalies in the second run were undetected in the first ILI, there would be 27 correct non-matches (CNM_2) and 23 incorrect ones relative to the second ILI run.

The mean matching accuracy metric, $\overline{ACC}$, can be formulated as follows:

$$\overline{ACC} = \frac{\left(\frac{CM + CNM_1}{N_1} + \frac{CM + CNM_2}{N_2}\right)}{2} \qquad (2)$$

Weighted accuracy might serve as a more appropriate metric, particularly when a notable discrepancy in anomaly counts between two runs exists. The tests

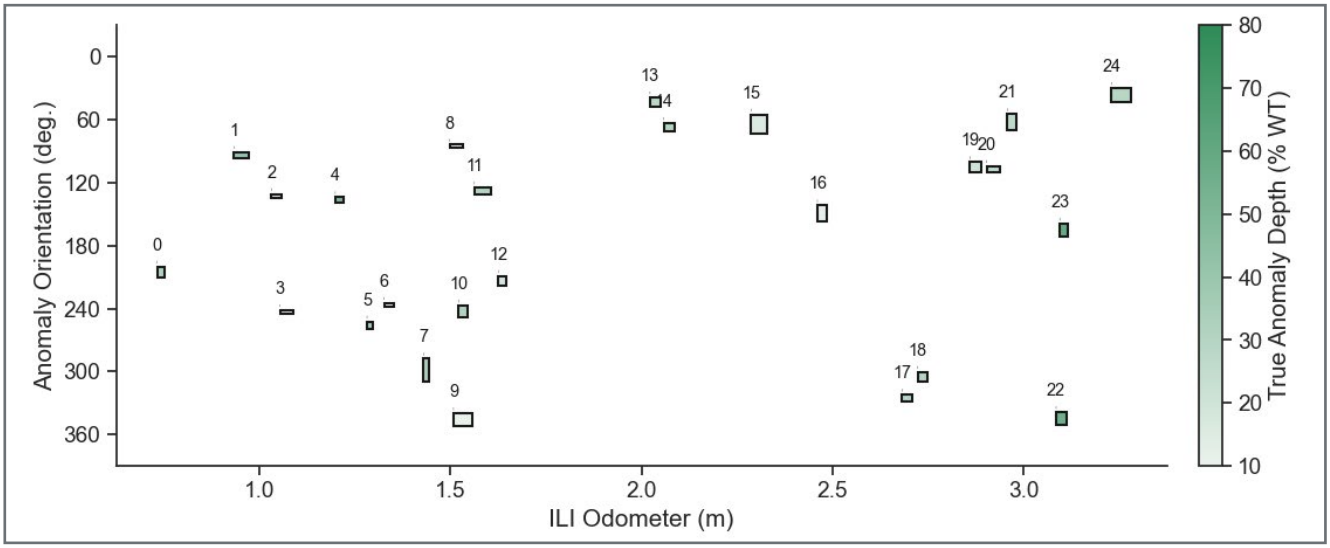

Figure 2: 25 Synthesized Anomalies.

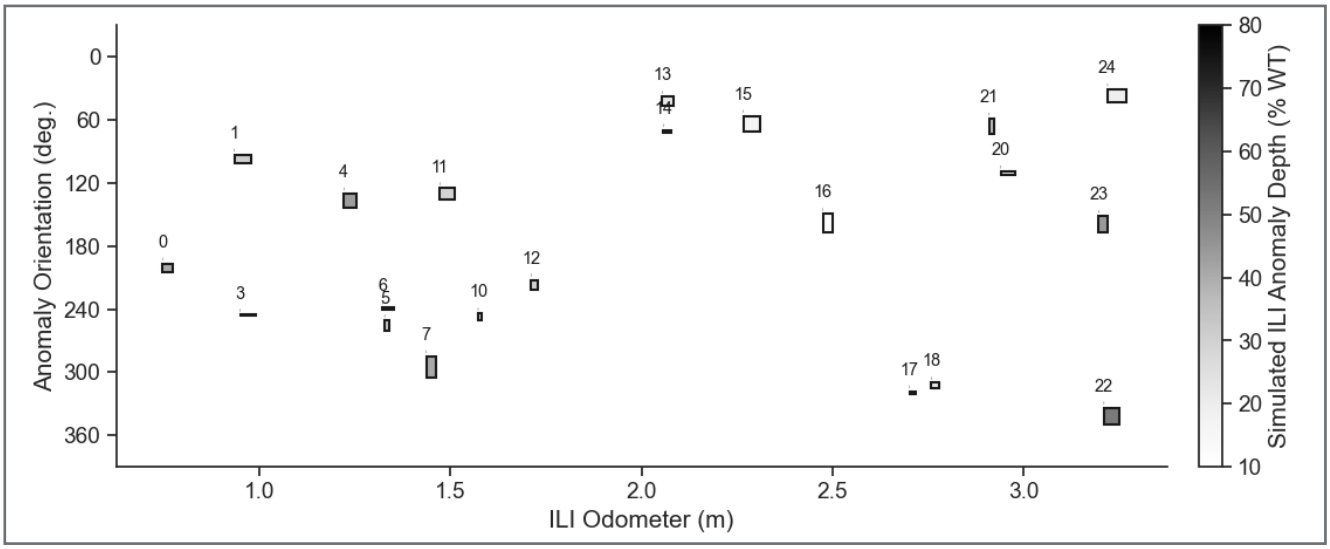

Figure 3: 1st Simulated ILI Run

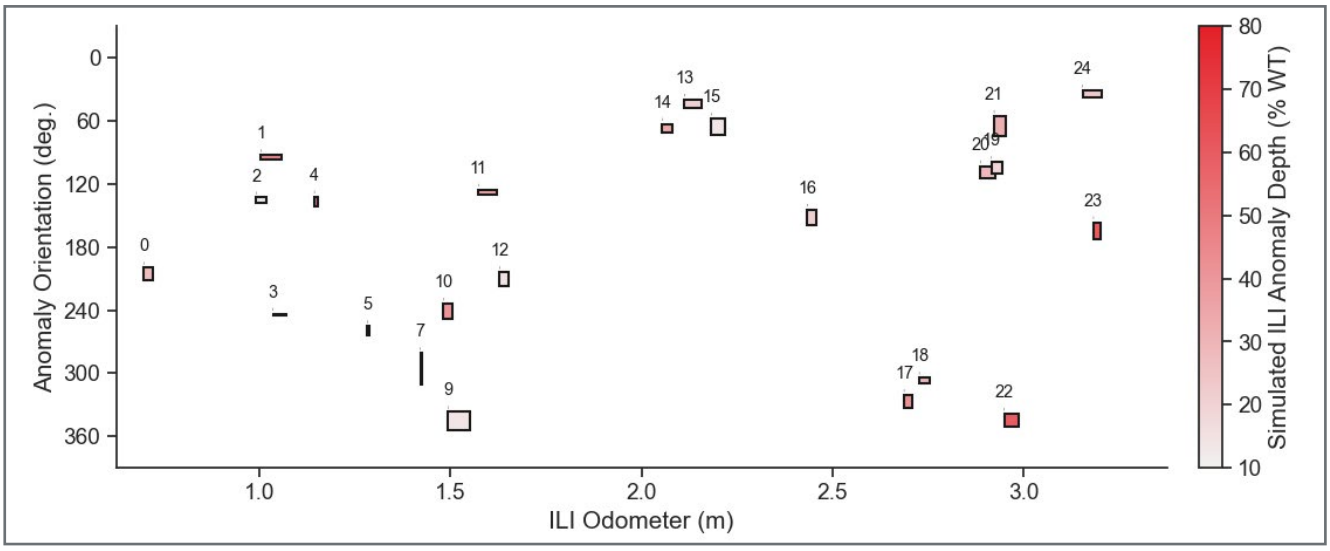

Figure 4: 2nd Simulated ILI Run

conducted thus far have maintained a consistent POD value across both simulated ILI runs, with the anomaly count per spool remaining approximately equal.

The RC algorithm's performance can be visualized through a heatmap, an example of which is presented in Figure 5. This heatmap displays match probabilities for each previous anomaly, serving as preliminary computations that precede the final classification decision. The anomalies intended for matching are depicted in Figure 3 and Figure 4. Black-edged rectangles highlight the correct matches, while arrowheads indicate the classifications made by the algorithm. From the visualization, the algorithm's performance seems almost optimal, as most arrowheads point to the correct match. It is noteworthy that:

- Anomaly IDs are not in a strict ascending order due to the added random location error.
- Anomaly number six from the previous set was correctly left unmatched since it was omitted in the second ILI run.
- Anomaly number 20 was incorrectly matched with the current anomaly 19, because higher probability was assigned to this label.
- Anomaly 22, present in both simulated ILI runs, was erroneously left unpaired due to the axial spacing between them.

4. Experimental Setup

The rigorous evaluation of machine learning systems is typically conducted through a process known as cross-validation [3]. In this process, the entirety of the available dataset undergoes multiple splits, segregating it into distinct parts: one for building model variants (training dataset), and the other for evaluating model performance (validation dataset). This approach tests the system's capacity for generalization, essentially its ability to produce accurate outputs for data that was not utilized during the training phase. The ultimate assessment of the model's performance is then based on its metrics over a separate dataset, known as the test set.

However, the KNN methodology developed in this context presents a unique scenario as it lacks parameters that require training. All settings are predetermined prior to conducting spool-wise classification inferences. Insights from the previous publication have been leveraged to approach an optimally performing algorithm configuration, and the evaluation results obtained with

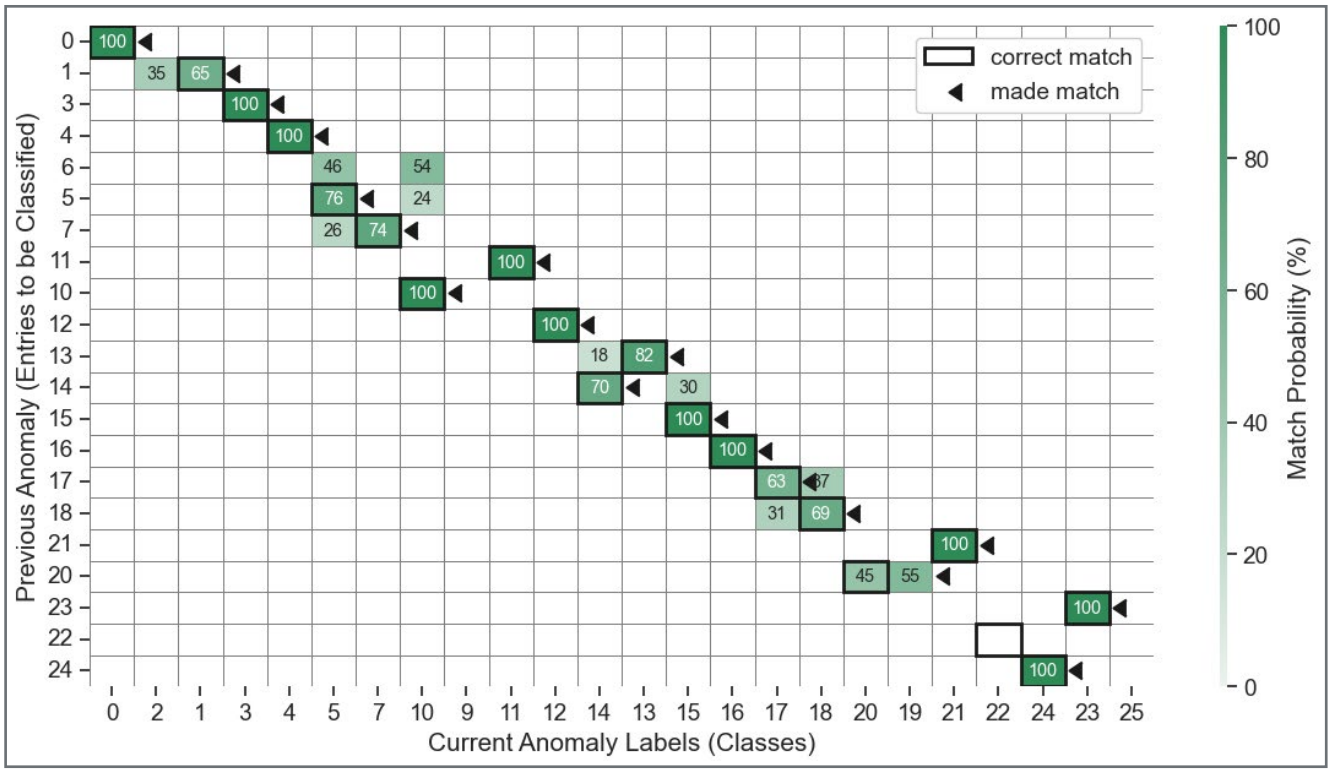

Figure 5: Visualization of Algorithm's Performance

this configuration are showcased in the current paper [2]. Given this scenario, all synthesized data records can be considered as part of the test set, providing a comprehensive basis for performance evaluation.

Synthetic data enables exploration of a wide range of scenarios. In this study, 2,000 20-inch spools were generated. Half of these spools featured anomalies uniformly distributed in both axial and circumferential directions, as depicted in Figure 6. The remaining spools exhibited anomalies uniformly distributed in the axial direction only, while following a normal distribution hoop-wise with a standard deviation set at 30 degrees, illustrated in Figure 7. As it was mentioned earlier, the synthesized true anomalies were programmed to avoid overlap. Nevertheless, during ILI simulation, which involves the addition of error to anomaly location, some ILI-simulated anomalies might overlap, introducing an additional layer of complexity for the algorithm.

The two subsets of 1,000 spools, distinguished by their circumferential anomaly distribution, consisted of 100 spools for each specified true anomaly count. These counts progressed in increments of 50, ranging from 100 to 550 anomalies per spool. Considering the probability of detection modelling, an average of 10% of the shallowest anomalies (as sized through simulated ILI) were removed from each spool. Initially, a total of 650,000 true anomalies were generated. After the simulation process, 585,001 anomalies remained in the first set of ILI results, each serving as a unique data

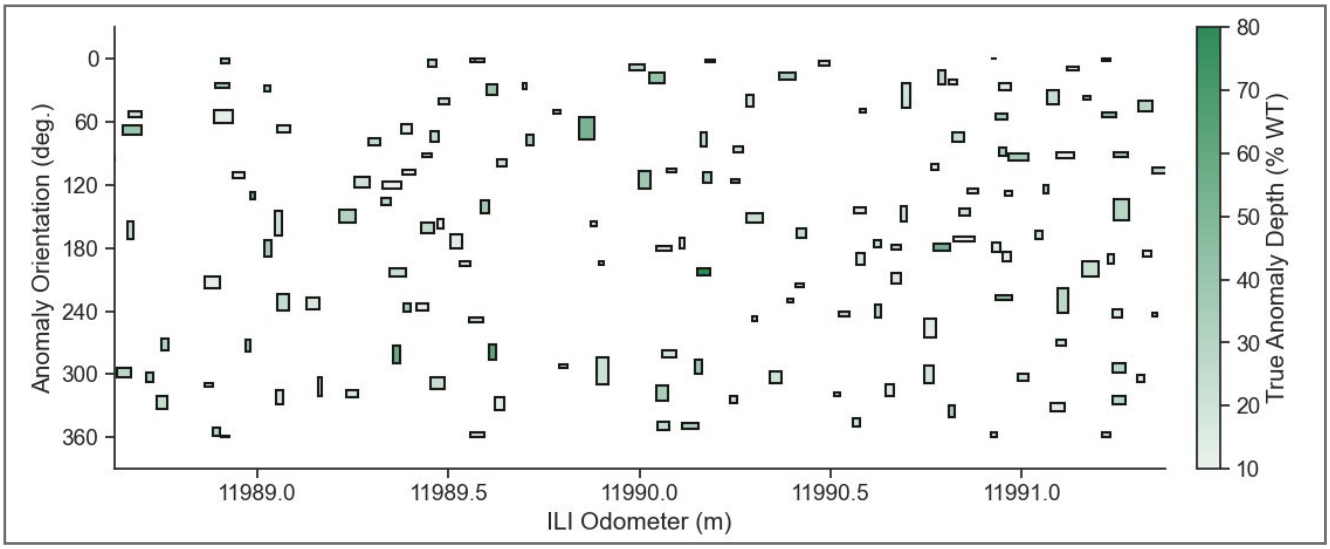

Figure 6: An interval along test spool with uniformly distributed synthesised anomalies

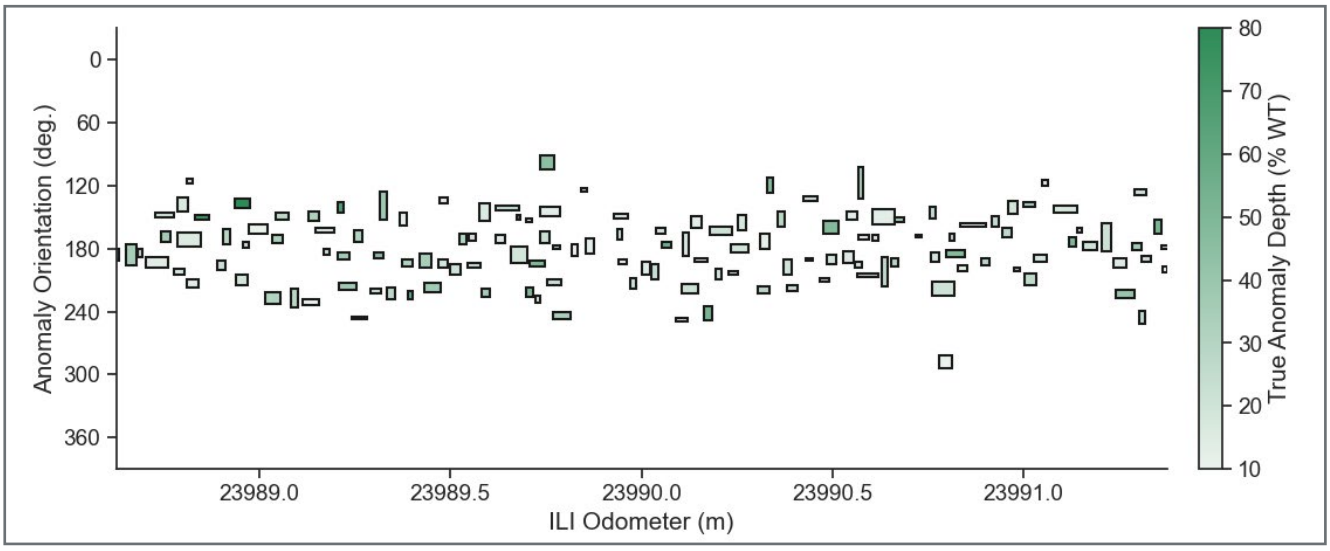

Figure 7: An interval along a test spool with normally distributed synthesised anomalies in hoop direction

entry for the subsequent algorithm validation. This dataset size marks a substantial expansion compared to the 163 data entries utilized in the initial study [2].

5. Validation Results

The mean accuracy statistics for each subset of 100 spools are presented in Figure 7, utilizing both violin and box plots for comprehensive visualization. Different subsets are discerned by colour, facilitating an easy comparison between uniformly and normally distributed anomalies. The x-axis of the plots denotes the mean anomaly counts, adjusted to reflect a POD, thus representing 90% of the true anomaly counts in each case. Several key observations and implications can be drawn:

- Trend with Increasing Anomaly Count for Uniform Circumferential Distribution: For uniformly distributed anomalies, the algorithm shows a high level of accuracy, with median accuracies consistently above 76%. There is a gradual decrease in accuracy as the anomaly count increases from approximately 89% to about 77%, yet the performance remains relatively robust.

- Trend with Increasing Anomaly Count for Normal Circumferential Distribution: In the case of anomalies distributed normally in the circumferential direction, the algorithm experiences a more significant drop in performance. The median accuracy starts at around 81% for lower anomaly counts and decreases to around 52% as the anomaly count increases. This suggests that the algorithm finds it more challenging to accurately match anomalies when they are concentrated in narrower circumferential regions.

- Variability and Consistency: The standard deviation of the mean accuracies across different subsets provides insight into the consistency of the algorithm's performance. For uniformly distributed anomalies, the standard deviation remains relatively low even as the anomaly count increases, indicating consistent performance. For normally distributed anomalies, the standard deviation is also low, but there is a slight increase as the anomaly count goes up, suggesting that the performance can vary more in these scenarios.

- Performance Extremes: The minimum and maximum values of accuracy across the subsets provide an understanding of the worst and best-case performance scenarios for the algorithm. Even in the worst-case scenarios, the algorithm maintains a decent level of accuracy, especially for uniformly distributed anomalies. The widest min-to-max differences are observed in subsets with smaller anomaly counts.

6. Discussion

While the established validation framework may initially appear to present a straightforward matching

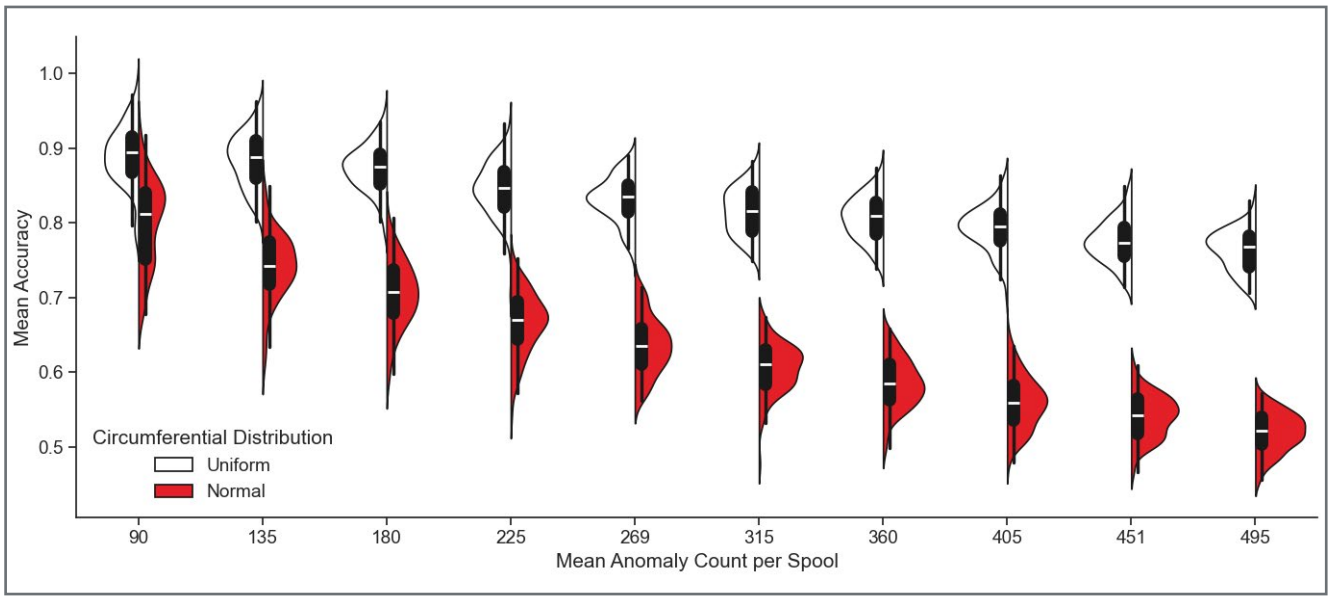

Figure 8: RC Algorithm's Validation Results

scenario due to the perfect alignment in weld-to-weld distance between two simulated ILI runs, it is important to note that potential spool-wise distance discrepancies in real-world run comparison can be addressed using an interpolation model. From a certain perspective, the synthesized data pose a more challenging case, as anomalies can overlap within a single set of ILI results due to the applied random ILI error. Such overlaps are not commonly observed in real-life ILI results, highlighting the harsh nature of the testing environment created for the evaluation.

Understanding the impact of anomaly distribution on algorithm performance is essential, particularly in practical contexts where anomaly distribution can significantly vary. These results highlight the necessity to take anomaly distribution into account when evaluating and optimizing RC algorithms, offering valuable insights for the algorithm's future refinement and enhancement. Nevertheless, it is imperative to ensure that the synthetic data utilized for evaluation authentically represent real-world conditions and the ILI tools' performance, to uphold the credibility of the evaluation outcomes.

7. Conclusion & Future Work

The comprehensive evaluation presented in this paper underscores the impact of anomaly distribution on the performance of run comparison algorithms, showcasing that both the quantity and spatial distribution of anomalies significantly influence accuracy. As the anomaly count increases, a noticeable decline in performance is observed, especially when anomalies are distributed normally in the circumferential direction. Despite these challenges, the algorithm maintains a commendable level of accuracy, even in worst-case scenarios.

Future work could focus on enhancing the algorithm's robustness and accuracy, especially in scenarios with high anomaly counts and density. Explorations into algorithm modifications or alternative approaches could yield improvements in performance and reliability. Moreover, there exists an opportunity to refine the validation framework, enhancing its capability to more accurately mirror the results obtained from actual ILIs. The exploration of additional matching scenarios could also contribute to a more complete understanding and refinement of the algorithm's functionality.

The insights gleaned from this study contribute significantly to the field, offering valuable guidance for the enhancement of RC algorithms and, by extension, the accuracy and reliability of corrosion growth rate assessments in pipeline systems.

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Monitoring and Anomaly Detection Approaches with AI and Data Analytics for Pipelines

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Abstract

Effective monitoring and anomaly detection are fundamental prerequisites for safeguarding the efficiency, integrity and reliability of pipeline systems. Here, we explore both physics-based and machine-learning approaches for operational asset monitoring and anomaly detection, as well as evaluate their performance and appropriateness across a selection of analytical challenges.

Specifically, we look at identifying and quantifying anomalies in pump performance and orifice plate alignment accuracy relating to work completed for British Pipeline Agency (BPA) and a prominent UK gas operator.

In this paper, we assess each method and its trade-offs and present their effectiveness as monitoring and anomaly detection approaches. We conclude that machine-learning in isolation is no replacement for engineering and physics expertise, so delivering physics-based insights overlaid with machine-machine learning is the best and most practical approach.

1. Introduction

Faced with rising operational costs and the need to reduce carbon emissions, pipeline operators must identify ways to enhance efficiency and minimise downtime while upholding safety. Anomaly detection in the form of condition monitoring is one promising solution.

Anomaly detection is the identification of rare items, events or observations which raise suspicions by differing significantly from most of the data. Condition monitoring is the identification of anomalies within machine performance. Any machine will eventually reach a point of poor health, be it rotating machinery (e.g., pumps, compressors) or not (e.g., orifice plates, valves). The wear and tear of everyday operation causes deterioration. While this may not manifest in output as extreme as an actual failure or shutdown, it will reach a point of suboptimal performance that will present in data anomalies. This signals the need for maintenance activity to restore the equipment to full operating potential.

In simple terms, identifying the "health state" falls into the domain of condition monitoring. The conventional approach entails scrutinizing individual sensor measurements and imposing minimum and maximum value limits. If the current value is within bounds, the machine is healthy; any deviation beyond these boundaries is deemed unhealthy and triggers an alarm. It is an approach that generates many false alarms and can miss a range of potential problems. False alarms not only waste time and effort but also reduce the availability of the equipment and lead to operator fatigue. Missed issues are more crucial as they can lead to equipment failure with the associated costs for repair and lost production.

Both problems share a common root cause: evaluating the health of complex equipment based on isolated measurements is inherently unreliable. A holistic approach is imperative, and there are two main methods: physics-based and machine-learning-based. Each method has its trade-offs, but our research has proved both to be effective monitoring and anomaly detection approaches. In this paper, we argue that while AI is an excellent tool for building experts out of data, it is no replacement for engineering and physics expertise. A physics-based approach with integrated machine-learning is best and the most practical for most pipelines in our experience.

2. Physics-based models: different techniques and findings

Here, we discuss the power and application of physics-based analytical approaches for finding, quantifying and identifying root causes of anomalies in pumping system performance in the context of work delivered for BPA. First, we discuss individual pumps and pump-sets, then move on to how the wider system and status of other assets impact this. Finally, we look more holistically, discussing how each pump is impacted by what liquid is being moved via which route.

2.1 Virtual Instrumentation (VI)

SCADA and data collection systems are designed with operations, regulatory compliance and safety in mind. Not only is real-time data access often a challenge, but the distribution of digitally accessible sensors is often inappropriate and/or inadequate for granular asset-by-asset analysis.

Virtual instruments are created to address this, filling gaps by simulating data sources required for analysis when they are physically lacking. It is done using data from nearby/hydraulically linked sensors and a good understanding of physics/fluid dynamics. Virtual instruments can then be derived from readily tailored general models. Common examples include apportioning the power consumption of various assets from a shared energy meter (see Figure 1) or computing the hydraulic contribution of pumps working together with shared pressure and flow meters. Building AI capable of performing on par or better than the physics-based models is possible, as they can naturally account for local effects, like pipe roughness. However, AI systems perform poorly unless trained on data specific to each VI deployment, which may not be available at sufficient quality or quantity.

2.2 Analysis of Individual pumps and pump-sets

While critical to operations, pumps are energy-intensive assets at scale. According to the US Department of Energy's Office of Industrial Technologies (OIT), pumping systems can account for up to 20-25% "of the energy usage in certain industrial plant operations"[1]

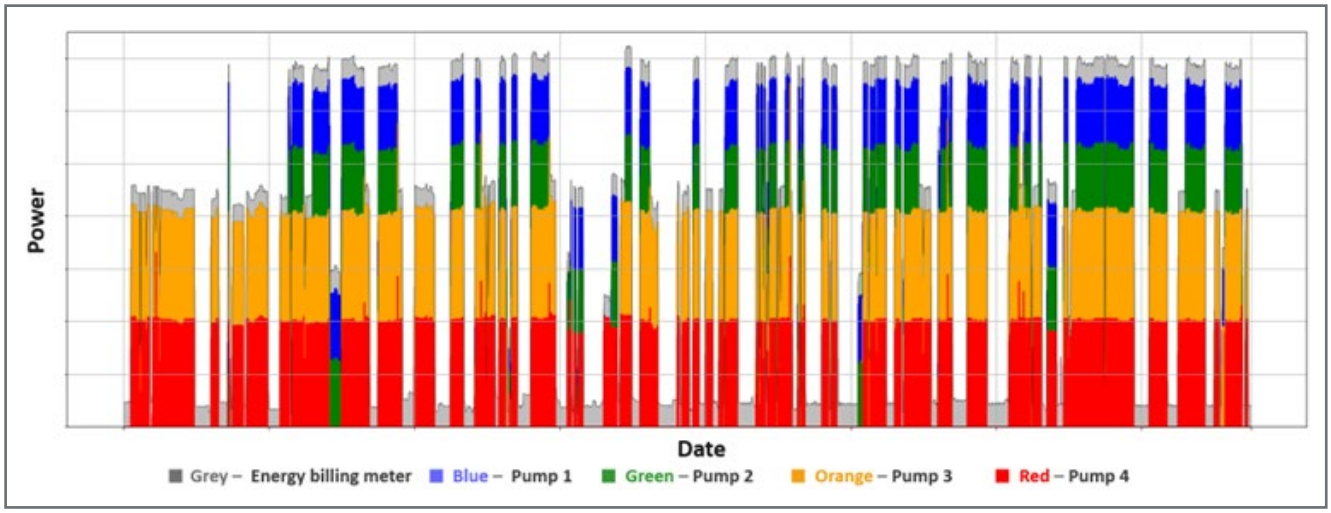

Figure 1: Anonymised example of an output from a virtual instrument. In this case, the power consumption of four mainline pumps has been calculated using the billing meter from a pumping station combined with a variety of other data sources and knowledge of the pump specifications.

Over time, energy usage increases as everyday wear and tear decreases efficiency. Identifying root causes for anomalous increases in energy consumption will keep pumps operating optimally for longer. Pump optimisation is worthwhile because energy consumption correlates with operating costs and carbon emissions, so optimised pumps increase productivity and profitability.

In principle, tracking, understanding and minimising this consumption is a straight-forward and simple exercise, but in practice can become quite complex. Firstly, VI is often required to examine performance on a per-pump basis. On multi-product lines, it is critical to identify what is being pumped so that density can be properly estimated. Not only is hydraulic power (and therefore efficiency) directly linked to the mass of fluid being moved, but changes in viscosity can significantly impact the system curve the pump experiences.

Computing the head versus flow (HvQ) for individual pumps is critical to evaluate whether they are appropriately sized for the required task. Performance can vary between different fluids, so it is important to identify different fluids. Over time, it is common for pumps to degrade and the pipeline system to become more resistive. This can move the pump away from its optimal pumping flowrate, harming efficiency and throughput. Analysis can also be performed on a pump-set basis in situations where multiple pumps can work together, either in series or parallel. This can enable operators to understand which pumping combinations work best on different fluids. Furthermore, this is a powerful tool when quantifying the impact of drag-reduction agent (DRA) as, for example, diesel dosed with DRA is effectively a new liquid.

2.3 Cross-correlation of pumps with other assets

Cross-correlation of pumping efficiency can be a powerful tool for identifying the root causes of anomalies. If there are two frequently observed efficiency ranges for a single pump, then it implies an operational issue rather than asset health. Correlating efficiency with the status of hydraulically linked assets like other pumps or valves can often identify the cause. Figure 2 illustrates a case where a pump was being throttled using a valve whenever it was hydraulically linked to a smaller pump upstream. The anomalous reduction in efficiency was substantial enough to justify pump replacement with a variable-speed drive for an excellent predicted ROI. Another interesting correlator can be temperature, in which temperature-driven viscosity changes impact pump performance enough to make it worthwhile to prioritize pumping at certain times of day when the conditions are ideal.

2.4 Product identification and tracking

Accurate knowledge of what fluid is where and when is already beneficial, but also unlocks additional analysis. No pump will achieve peak efficiency for multiple disparate liquids, so this disparity is worth quantifying.

Identifying a specific fluid can be done in various ways. Density data is often available, so the expected density for each potential fluid option can be computed and compared to the measured density using temperature.

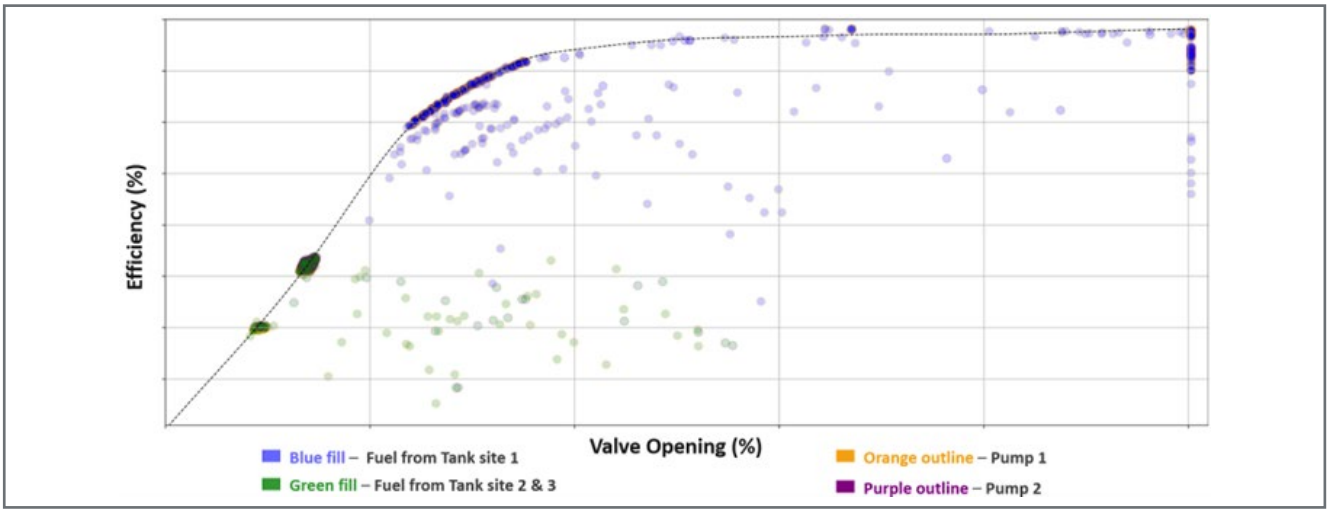

Figure 2: Anonymised example of an anomaly in pumping efficiency having its root cause identified via cross-correlation techniques. In this instance a downstream valve was being sub-optimally employed to throttle the pump.

The fluid f with the lowest difference can be selected, as shown in eq1. A simple linear model is typically adequate for the temperature compensation.

(eq1)

$$diff = ABS \sum_{f=1}^{n} measured\_density - \left[density_{@T0}^{f} + (coeff * (T - T0)\right]$$

Alternative methods using datums like opacity can be used in a similar way. If data is lacking, then more creative approaches, such as observing the temperature rise of a fluid as it passes through a pump and using liquid heat capacity, can be considered. However, they are far less reliable.

Once the liquid is identified, dead-reckoning approaches can be highly accurate, provided pipe diameters are known and thermal expansion is compensated for. More complex models can integrate valve statuses and flow meters to determine which routes a particular parcel of liquid has taken.

2.5 Breaking complex networks into legs and routes for a granular analysis

Pump performance depends highly upon the wider system. A carefully designed system with optimally sized pumps may change significantly over time. Changes in pumped products, asset degradation/renovation, expansions or closures within the network can impact a system curve. A pump selected to serve multiple routes from source to destination will either serve one route optimally or exhibit broad mediocre performance. An exception is pumps paired with a variable speed drive. Discovering the optimal speed for each liquid/route combination to minimise cost-per-tonne delivered is non-trivial.

Pump optimisation is ideally performed for each system curve (route and liquid combination). For complete analysis, data must be sorted based on each system curve encountered. This process can be somewhat laborious, necessitating semi-bespoke software to scrutinise datasets – including flow, pressure, density, liquid type and valve status.

Once operational conditions are understood, analytical means can compute various beneficial metrics. Most critical for optimisation would be the HvQ curves for each condition and their associated energy-cost-per-throughput. Armed with this information, it becomes an engineering opportunity to decide on optimisation techniques, such as drag reduction agents, changes to RPM profiles or asset refurbishment/replacement. The benefits of identifying root cause of anomalies in pumping system performance are clear: if operators know the optimal route or time to pump, they can lower energy usage and reduce operating costs while maintaining throughput. We have seen reductions in energy consumption of around 20% when delivering the same product to the same destination by identifying the most cost-effective route to serve that destination (see Figure 3). Of course, operational requirements often preclude the total prioritisation of an optimal route, and many pipelines lack the complexity to make this worthwhile. For complex multi-product systems, the analysis described here can be extremely impactful and lay the foundations for significant cost savings.

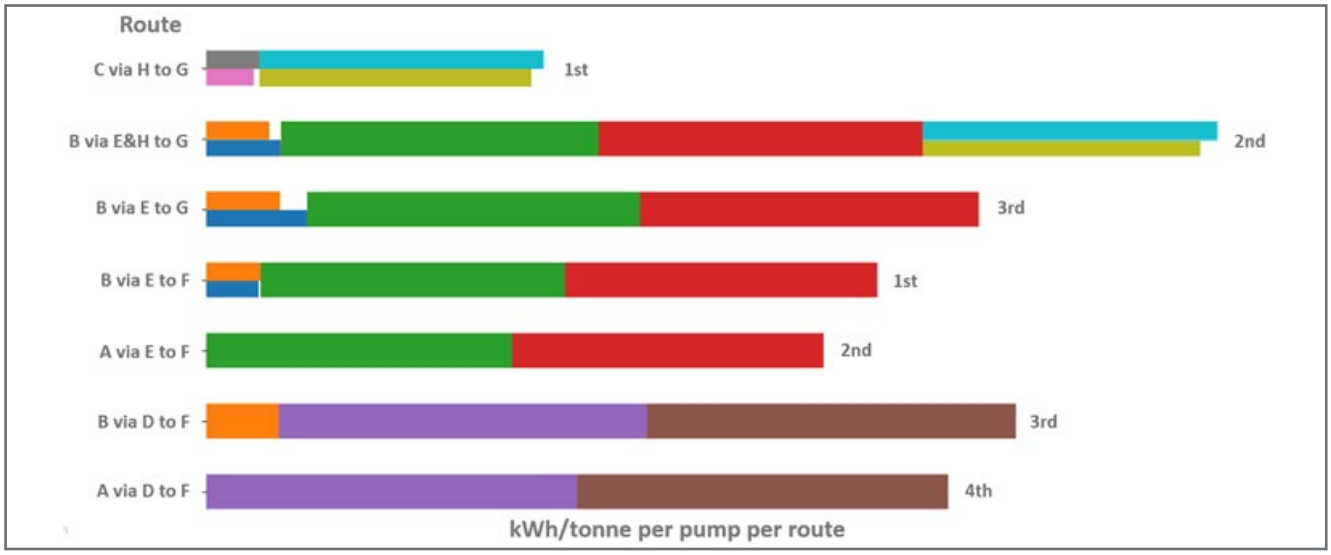

Figure 3: Anonymised example of per-pump per-route analysis output. Shows energy cost contribution of each pump (different colours) which contributes towards serving a particular route. Routes are ordered (and labelled) by their average throughput per destination.

3. Machine-learning approaches for anomaly detection

At the other end of the spectrum from physics-based monitoring and optimisation techniques are more statistical, machine-learned approaches. We have explored various methods, including vector machines and kernel density-based methods. For the pipeline industry, we have focussed on two: first, multivariate statistical analysis using Principal Component Analysis (PCA) and the Mahalanobis Distance (MD), and second, artificial neural networks (specifically autoencoder networks) learning efficient data representations by compressing sensor readings. Both proved effective anomaly detection methods for condition monitoring when applied to the orifice plate data of a leading UK gas operator, but each has its respective strengths and trade-offs.

3.1 Approach 1: multivariate statistical analysis

Dimensionality reduction using principal component analysis

For identifying anomalies when dealing with one or two variables, data visualisation can often be a good starting point (as discussed in the previous section). When scaling this up to high-dimensional data, which is often the case in practice, this approach becomes increasingly difficult. Fortunately, multivariate statistics can help.

As dealing with high dimensional data is often challenging, there are techniques to reduce the number of variables (dimensionality reduction). One of the main ones is Principal Component Analysis (PCA), which performs a linear mapping of the data to a lower-dimensional space in such a way as to maximise the variance of the data in the low-dimensional representation. In practice, the covariance matrix of the data is constructed, and the eigenvectors of this matrix are computed. The eigenvectors that correspond to the largest eigenvalues (the principal components) can now be used to reconstruct a large fraction of the variance of the original data. The original feature space has now been reduced (with some data loss, but hopefully retaining the most important variance) to the space spanned by a few eigenvectors.

Multivariate anomaly detection

When dealing with a collection of data points, they will typically have a certain distribution (e.g. a Gaussian distribution). To detect anomalies more quantitatively, first calculate the probability distribution $p(x)$ from the data points. With new examples (x), compare $p(x)$ with a threshold r. If $p(x)<r$, it is considered an anomaly. Normal examples tend to have a large $p(x)$, while anomalous examples tend to have a small $p(x)$.

In the context of asset health monitoring, this is interesting because anomalies can tell us something about the "health state" of the monitored equipment. Data generated when the equipment approaches failure or during sub-optimal operation will exhibit a different data distribution from "healthy" equipment.

The Mahalonabis Distance

Consider the problem of estimating the probability that a data point belongs to a distribution, as described above. Our first step would be to find the centroid or centre of mass(s) of the sample points. Intuitively, the closer the point is to this centre of mass, the more likely it is to belong to the set. However, we also need to know if the set is spread out over a large range or a small range so that we can decide whether a given distance from the centre is noteworthy or not. The simplistic approach is to estimate the standard deviation of the distances of the sample points from the centre of mass. By plugging this into the normal distribution, we can derive the probability of the data point belonging to the same distribution. A significant proportion of SCADA data turns out to be non-Gaussian (bimodal). We have evaluated methods for kernel density estimation to drive our knowledge of the data distribution and support vector machine techniques on the same data set. All methods mentioned in this paper can produce alerts for anomaly detection.

Were the distribution decidedly non-spherical, for instance, ellipsoidal, then we would expect the probability of the test point belonging to the set to depend not only on the distance from the centre of mass but also on the direction. In those directions where the ellipsoid has a short axis, the test point must be closer, while in those where the axis is long, the test point can be further away from the centre. Putting this on a mathematical basis, the ellipsoid that best represents the set's probability distribution can be estimated by calculating the covariance matrix of the samples. The Mahalanobis distance is the distance of the test point from the centre of mass divided by the width of the ellipsoid in the direction of the test point. The drawback of the above approach is that, in reality, many acceptable distributions are often non-spherical, requiring additional thought into precisely how the boundary is drawn. Neglecting the careful creation of the boundary will lead to a high error rate, even with an otherwise well designed and trained model computing the Mahalonabis distance.[2] computing Mahalonabis distance.[3]

To use the Mahalanobis distance to classify a test point as belonging to one of the N classes, one first estimates the covariance matrix of each class, usually based on samples known to belong to each class. In our case, as we are only interested in classifying "normal" vs "anomaly", we use training data that only contains normal operating conditions to calculate the covariance matrix. Then, given a test sample, we compute the Mahalanobis distance to the "normal" class and classify the test point as an "anomaly" if the distance is above a certain threshold.

3.2 Approach 2: artificial neural networks

The second approach uses autoencoder neural networks[4] It uses similar principles as the above statistical analysis but with slight differences. Fundamentally, the goal is an AI capable of independently predicting 'normal' behaviour of an asset for various operational conditions. If the actual behaviour differs from the predicted norm, this can be investigated.

An autoencoder is an artificial neural network used to learn efficient data codings unsupervised. An autoencoder aims to learn a representation (encoding) for a set of data, typically for dimensionality reduction. Along with the reduction side, a reconstructing side is learnt, where the autoencoder tries to generate from the reduced encoding a representation as close as possible to its original input. Architecturally, the simplest form of an autoencoder is a feedforward, non-recurrent neural network very similar to the many single-layer perceptrons, which makes a multilayer perceptron (MLP) — having an input layer, an output layer and one or more hidden layers connecting them — but with the output layer having the same number of nodes as the input layer, and with the purpose of reconstructing its own inputs.

For anomaly detection and condition monitoring, the basic idea is to use the autoencoder network to "compress" the sensor readings to a lower-dimensional representation, which captures the correlations and interactions between the various variables. (Essentially, the same principle as the PCA model, but allowing for non-linear interactions between the variables).

The autoencoder network is then trained on data representing the "normal" operating state to compress and reconstruct the input variables. During the dimensionality reduction, the network learns the interactions between the various variables and should be able to reconstruct them back to the original variables

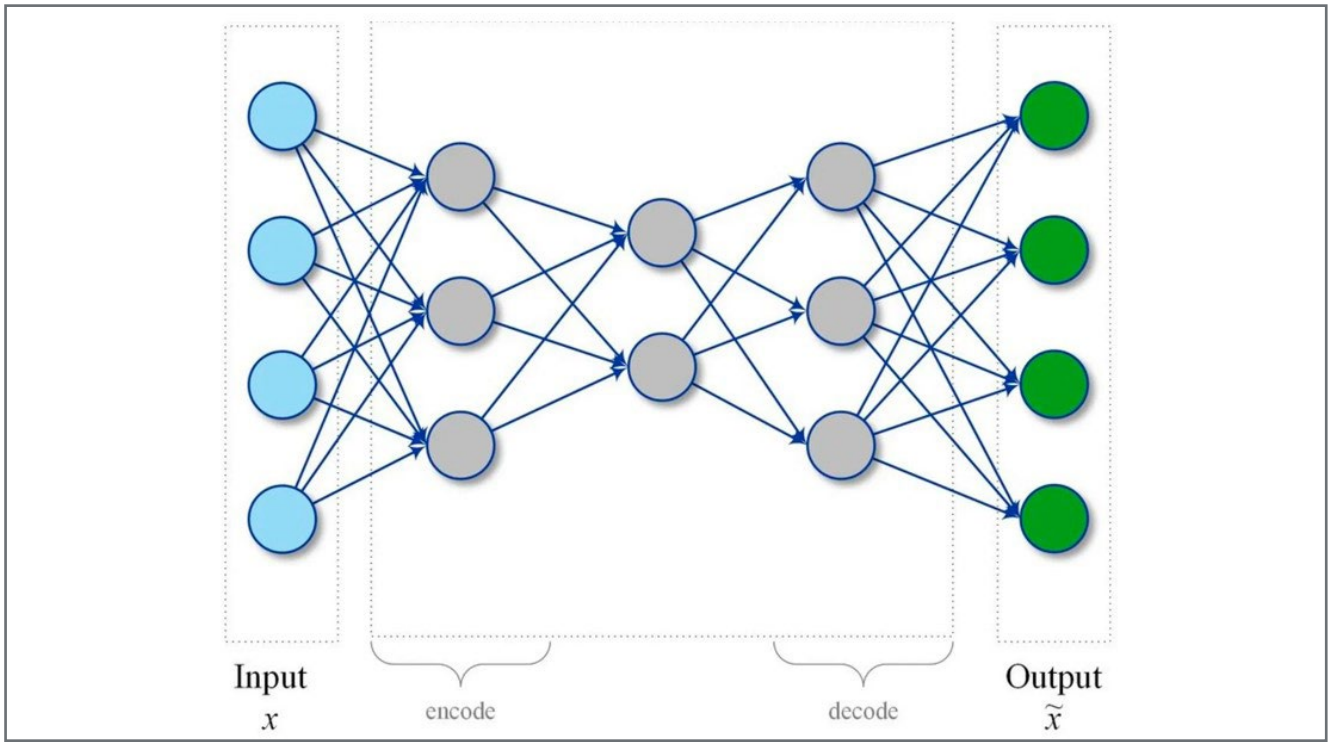

Figure 4: Illustration of Autoencoder network.

at the output. The main idea is that as the monitored equipment degrades, this should affect the interaction between the variables (e.g. changes in temperatures, pressures, vibrations).

As a pipeline operates, you will see an increased error in the network's reconstruction of the input variables. Monitoring the reconstruction error gives an indication of the "health" of the monitored equipment, as this error will increase as the equipment degrades. Similar to the first approach of using the Mahalanobis distance, it uses the probability distribution of the reconstruction error to identify whether a data point is normal or anomalous.

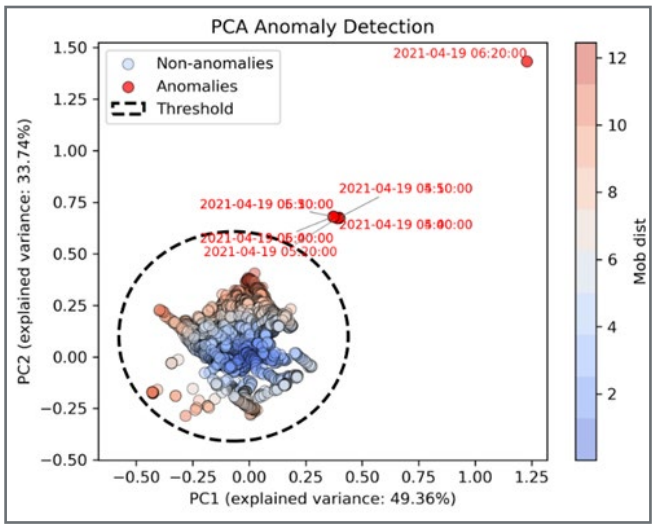

Figure 5: An example of PCA anomaly detection.

3.3 Opportunities for deployment

Using the sample data of data provided by the pipeline operator, we demonstrated that both methods detect anomalies in the data, although each method has its trade-offs: PCA+MD is sensitive to the size of the input dataset and train/test split, while Autoencoders will produce results irrespective of the input data, so extra care needs to be taken to scale and apply appropriate weights to the incoming data based on physical constraints. The best methods for pipeline monitoring and optimisation are determined by physics and data collection and not by the complexity of the machine-learning techniques.

In this instance, our analysis focused on orifice plate monitoring. The operator uses orifice plates for fiscal metering, but incidents had occurred following incorrect installation post-calibration. Such incidents risk billing errors or compromised safety if pressure is adjusted according to incorrect flow measurements. Anomaly detection helps mitigate these risks, providing confidence in equipment and lessening the likelihood of costly malfunctions going undetected, while improving maintenance scheduling for reduced costs and maximised ROI.

4. Conclusion

It is critical to maintain pipeline efficiency from the perspectives of operations, environmental impact and cost. Effective condition monitoring and anomaly detection technologies should be imperative for all pipeline operators. The commercial benefits are numerous, including reduced energy consumption, increased efficiency and lower operational expenditure. Findings from our work with BPA revealed that, for the section of their network we examined, the average mainline pump would consume approximately £5,000 less energy each month by raising its efficiency to as-new optimal levels.

Our exploration into anomaly detection approaches has demonstrated that both physics-based and machine-learning methods hold value. While machine-learning relies on the collection of vast volumes of data and the execution of diverse algorithms, the absence of a profound understanding of the underlying physics will always limit its efficacy.

In our view, the best and most practical approach is a hybrid one: delivering physics-based insights overlaid with machine learning. While machine-learning is an excellent tool for building experts out of data, it is no replacement for engineering and physics expertise. By combining the deterministic reliability of physics-based methods with the adaptability and locally nuanced character of machine-learning, you leverage the strengths of both approaches to deliver optimal anomaly detection.

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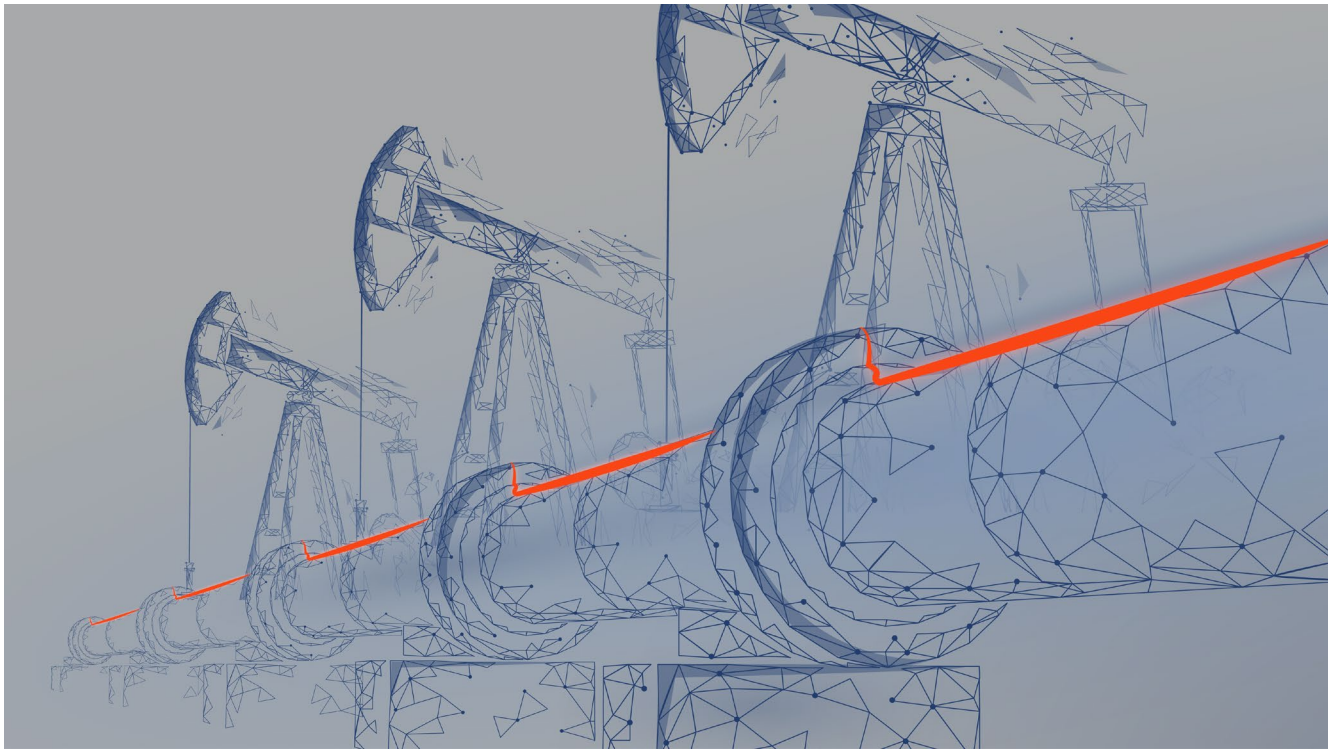

Distributed Fiber Optic Sensing for Leak Detection: Tuning, field-testing and the future

A. MURRAY > LUNA INNOVATIONS

Abstract

Distributed Fiber Optic Sensing is a highly sensitive technology for leak detection that can provide rapid detection and precise locating of small leaks. The evidence from field trials and real-world leaks is becoming increasingly available and more and more pipelines are implementing the technology for leak detection. Under controlled testing, it is trivial to identify the effects of a leak. But what about on deployed systems? In this article, we will discuss how these systems can be tuned in the field – where the sensitivity of the fiber can vary with the installation and local environment, and how field-testing can be performed on an ongoing basis to validate performance. We will also briefly consider how Machine Learning and Artificial Intelligence might impact leak detection using fiber in the future.

1. Introduction

Leak Detection is a concern for most pipeline owners and operators for a multitude of reasons. From the loss of product, pipeline damage, the environmental and health concerns, and the large costs associated with rectifying problems, it is clearly in the interest of all involved parties to minimise the impact of any leaks that occur. Over the past few decades Distributed Fiber Optic Sensing (DFOS) has been deployed in a wide variety of industries and as more evidence comes to light regarding the specific benefits and advantages of DFOS it is being increasingly deployed as Fiber Optic Fiber Leak Detection Systems (FOLDS).

2. DFOS Overview

DFOS covers a remarkable set of technologies that convert optical fibers into distributed arrays of thousands of virtual sensors that provide real-time monitoring along the entire length of a pipeline asset. The appeal lies in the high spatial resolution, fast response, high sensitivity and lack of power requirements along the length of the fiber[1].

At its simplest, DFOS involves launching pulses of laser light into a fiber and monitors properties of the small fraction of light that is scattered back down the fiber. The light can be scattered by different scattering mechanisms (Figure 1) that allow different physical effects such as strain, temperature, and vibrations to be monitored. For the purposes of leak detection there are two technologies at the forefront: Distributed Acoustic Sensing (DAS) and Distributed Temperature Sensing (DTS).

3. DTS

Of the two, DTS is the more straightforward technology in that it can be used to detect one parameter: the temperature at regular intervals along the entire length of the fiber. As such, it is clearly suited to identifying sections of a pipeline that are experiencing unexpected temperature changes. Unsurprisingly, DTS is really only suitable for pipelines where the leaking product is expected to cause a significant thermal effect. This could be products that are transported significantly above or below ambient temperature (e.g., LNG, Liquid Ammonia), or those that will undergo significant thermal changes arising from the Joule-Thompson effect when leaking from a pipe (e.g., CO_2).

A significant delta doesn't guarantee a rapid response – the thermal effect is still governed by the time taken for the effect to permeate through to the fiber. On one LNG pipeline - a product typically transported at extremely low temperatures (-160°C) – despite the large temperature delta the temperature of the fiber dropped from 30°C at a low rate of - 1°C/hr until it reached 0°C (Figure 2). While the response in this example was quite slow, it could have been significantly improved with optimisation of the cable installation[2].

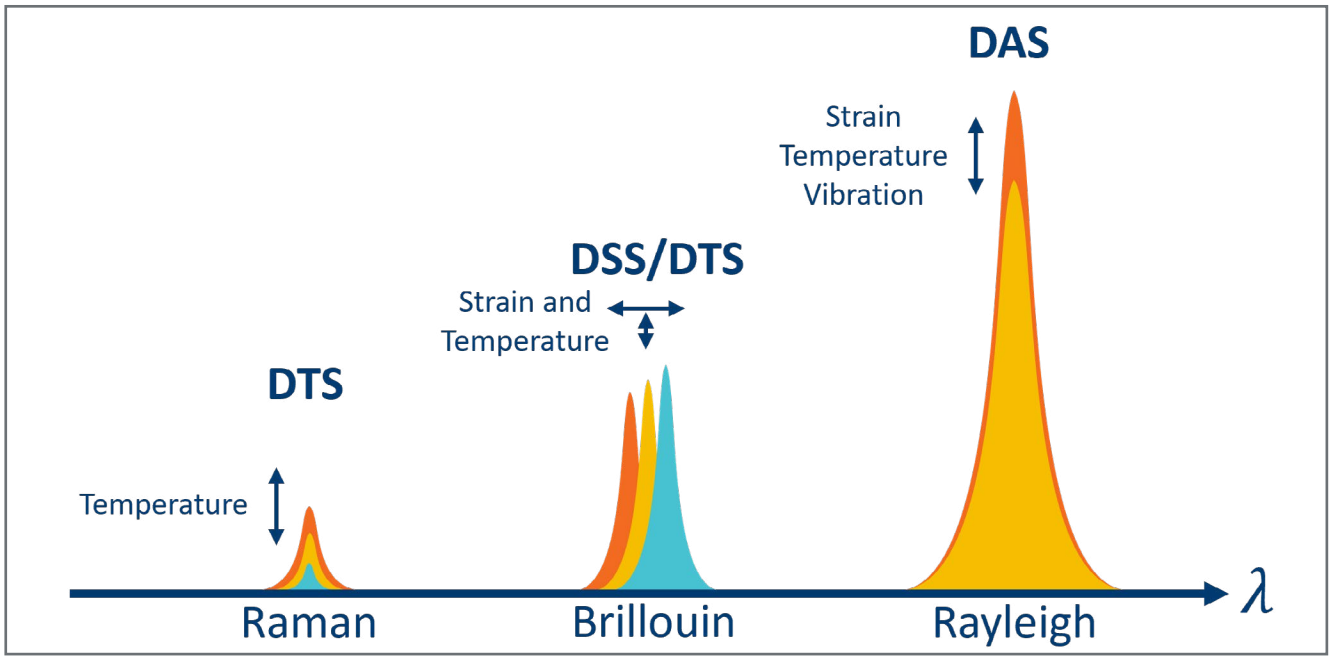

Figure 1: Representation of the different scattering phenomena that can be used for Distributed Fiber Optic Sensing

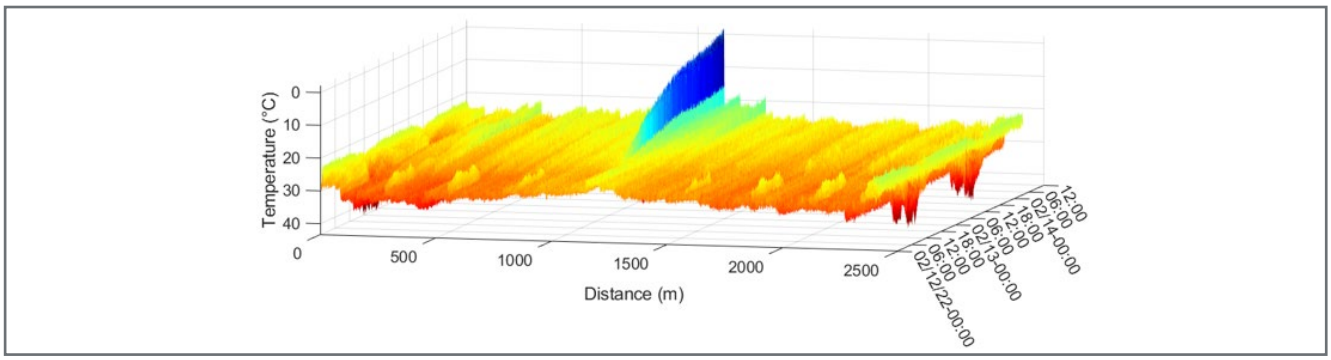

Figure 2: DTS response from an LNG leak showing a clear thermal response at the leak location.

3.1 DTS Tuning

With only a single measurand to consider, the temperature reported by the fibre, determination of the detector configuration for a DTS system is largely an exercise to identify what thermal effects are expected to occur and what detection criteria to implement. Basic detection criteria include whether an absolute temperature value has been reached or whether a particular thermal gradient is observed. Extending the data further, it is possible to consider whether a localised temperature delta is anomalous compared to the average temperature of a surrounding area. As ever, the aim with any tuning is to achieve detection capability in as little time as possible while minimising the nuisance alert rate. Natural variations in the background environment will determine how responsive a DTS system can be made and after a short period of monitoring the day-to-day effects will be relatively well understood.

4. DAS

Light that has undergone Rayleigh scattering forms the basis of DAS, which is uniquely sensitive to strain, temperature, and vibration simultaneously. DAS systems come in two forms: (amplitude-based) Intensity-DAS and (phase-based) Quantitative-DAS. Intensity-DAS has been the basis for many deployed systems, but Quantitative DAS is the superior technology. While quantitative-DAS has been implemented in some industries such as seismic and well monitoring, the operational range and hardware costs were prohibitive to wider deployment. That is changing now, with quantitative-DAS systems exceeding the ranges possible with Intensity-DAS and providing a step change in the quality of data that can be obtained. For the purposes of pipeline leak detection, there are 4 distinct physical effects that can be identified.

4.1 Negative Pressure Pulse (NPP)

In a pressurised pipeline, at the instant that a new leak develops there is a sudden loss of pressure at the location of the leak. A pressure wave is formed that propagates through the pipeline at the speed of sound of the product (typically hundreds to thousands of metres per second). Critically, the external effect of this pressure wave is detectable with DAS and an NPP produces a distinctive V-shape signal originating at the leak location (Figure 3).

4.2 Orifice Noise (OFN)

As the product is forced out of a pipeline it produces vibrations that are coupled through to the fiber. Outside of the trivial situation where the product is impacting directly onto the fiber, these signals will couple through any solids directly in contact with the fiber. Figure 4 shows the OFN signal arising on a buried pipeline from a leak (~115 L/min) detected on a fiber approximately 1 m away. For an above ground pipeline, the fiber needs to be directly in contact with the pipeline to be affected by these vibrations while for a buried pipeline the vibrations will couple through the surrounding ground.

4.3 Ground Heave / Strain

Primarily observed on pipelines where the product expands rapidly when no longer confined inside the pipeline and induces strain onto the fiber. However, this phenomenon could also be detected on buried liquid pipelines where the ground is washed away leading to a strain on the fiber. Figure 5 shows the movement of ground heave arising from a gas leak injection test. This type of ground movement induces signals in the fiber that are detectable with DAS.

4.4 Distributed Temperature Gradient Sensing (DTGS)

A leak that induces thermal changes in the area around the fiber will produce a detectable signal. The effect

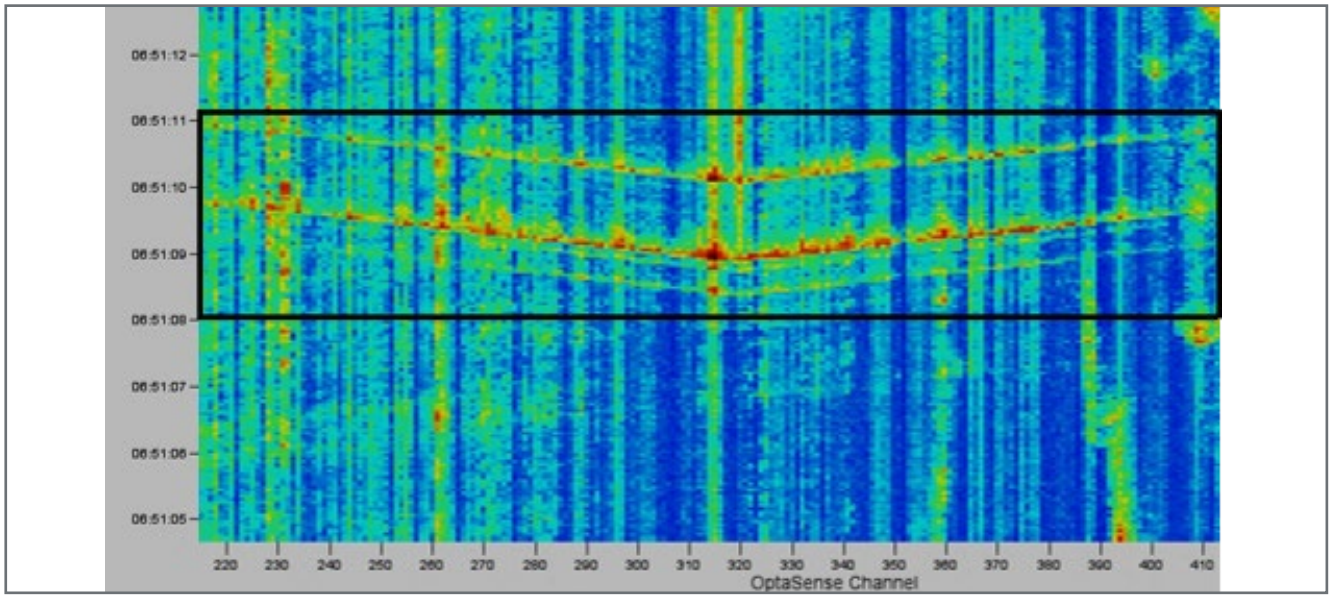

Figure 3: Distinctive V-shape signals indicative of NPP events arising from genuine leak on a slurry pipeline.
The channels on the x-axis represent the distance along the fibre, approximately 3.15km.

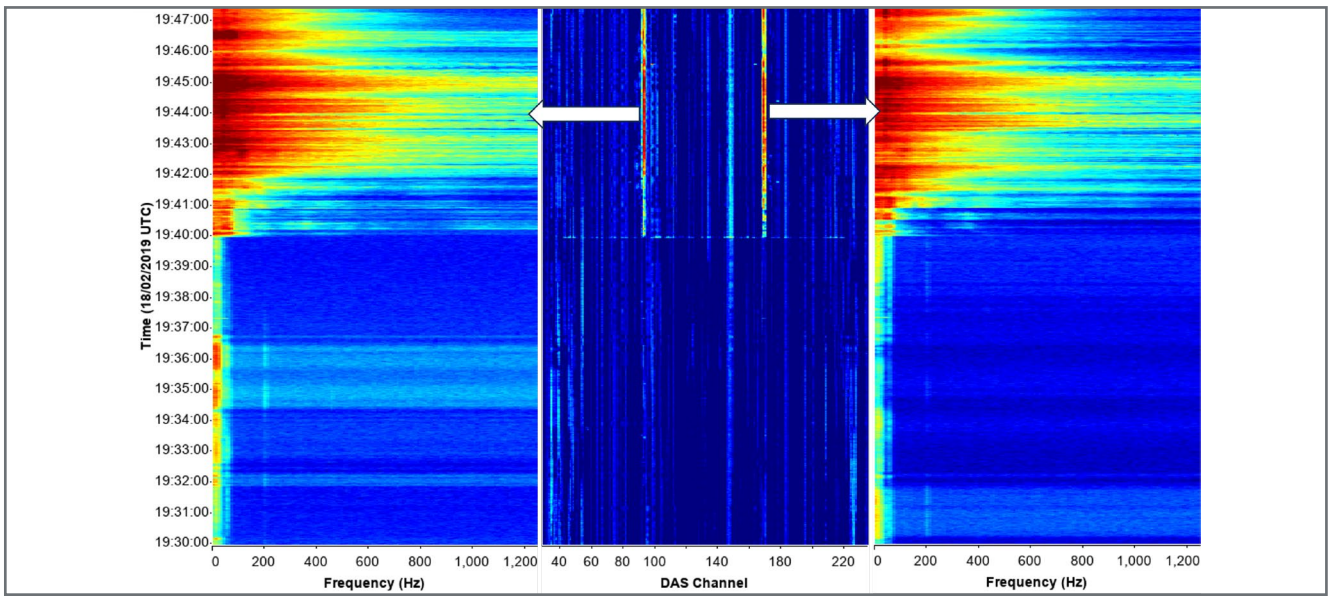

Figure 4: OFN signal arising from 115 L/min liquid leak detected on a fiber approximately 1m away from the leak. The central panel shows a time-space waterfall plot with two vertical red signals indicating the leak event. Two signals are generated because the fiber passes the leak location twice. The left and right panels show the spectral content of the signal from the location of the leak.

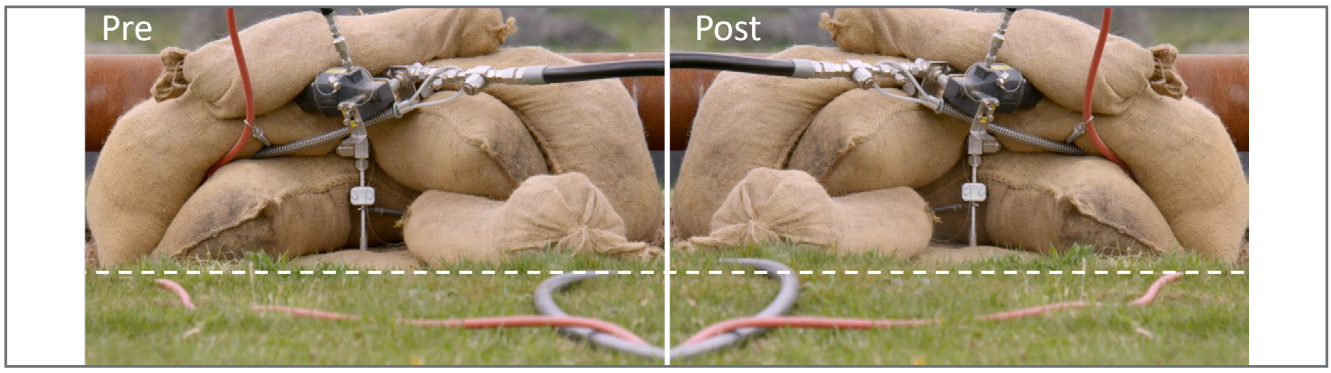

Figure 5: Ground Heave event arising from a gas leak injection test. The horizontal dashed line can be used to see the subtle heave in the ground. The effect is clearer in the slow-motion video available at https://public.huddle.com/a/WxLrZdP/index.html

can be identified with intensity-DAS but is more apparent with quantitative-DAS with systems being sensitive to millikelvin temperature changes. DTGS effects tend to occur over longer timescales because of the time taken for thermal effects to reach the fiber.

In a test where a heat source was placed on the ground, the thermal effect arising on a fiber (at a depth of 0.5 m) was clearly observed (Figure 6). The effect corresponds to a ~0.5°C increase in the temperature of the fiber over a period of 40 minutes before the heater was switched off and the ground cooled. The impulses seen prior to the heating and cooling effects correspond with acoustic signals arising from the heater being switched on and off. It is here that DAS stands out compared to DTS systems because the sensitivity and stability of the effect arising from a temperature change is unparalleled. While DAS is significantly more sensitive, it does not produce an absolute temperature measurement and so combining the two technologies into a complementary leak detection system can significantly enhance capability.

4.5 Performance

The four components can be split into two with OFN, Strain and DTGS forming one group comprising effects that occur over longer timescales and are generally localised to the location of the leak. NPP stands aloneas an effect that can be detected near instantaneously after the onset of a leak and can affect many km of pipeline. While the effect has a large spatial component, the apex of the characteristic 'V' shape will always originate at the leak itself, allowing it to be located with a high degree of accuracy. Each of these effects can be combined together to adapt to the specifics of each pipeline and maximise the confidence in a detected leak[3].

With many years of experience, numerous leak trials, and evidence from real-world leaks the typical performance that is expected of a DAS system is detailed in Table 1 showing the high sensitivity, fast response and detailed leak location accuracy. Note that the leak performance is generally expressed as the magnitude of the leak itself rather than the more conventional industry expectation of percentage of flow. This is because the system is reliant on detection of the external effects of the leak itself, which are largely unrelated to the amount of product flowing in the pipeline itself.

The particulars of each fibre installation along a pipeline will affect how DAS systems perform: the proximity of the fiber, whether the pipeline is above ground or buried, the type of fiber and whether it is installed in conduit, the local environment around the pipeline, and more. This inevitably means that the performance of no two systems is fixed and may also vary along the length of a pipeline itself. While this may not seem overly reassuring, it must be considered in the context that DFOS is significantly more sensitive, more responsive and provides more precise location accuracy than conventional leak detection systems.

In recent years, and after considerable efforts being placed into demonstrating the viability, DAS has seen

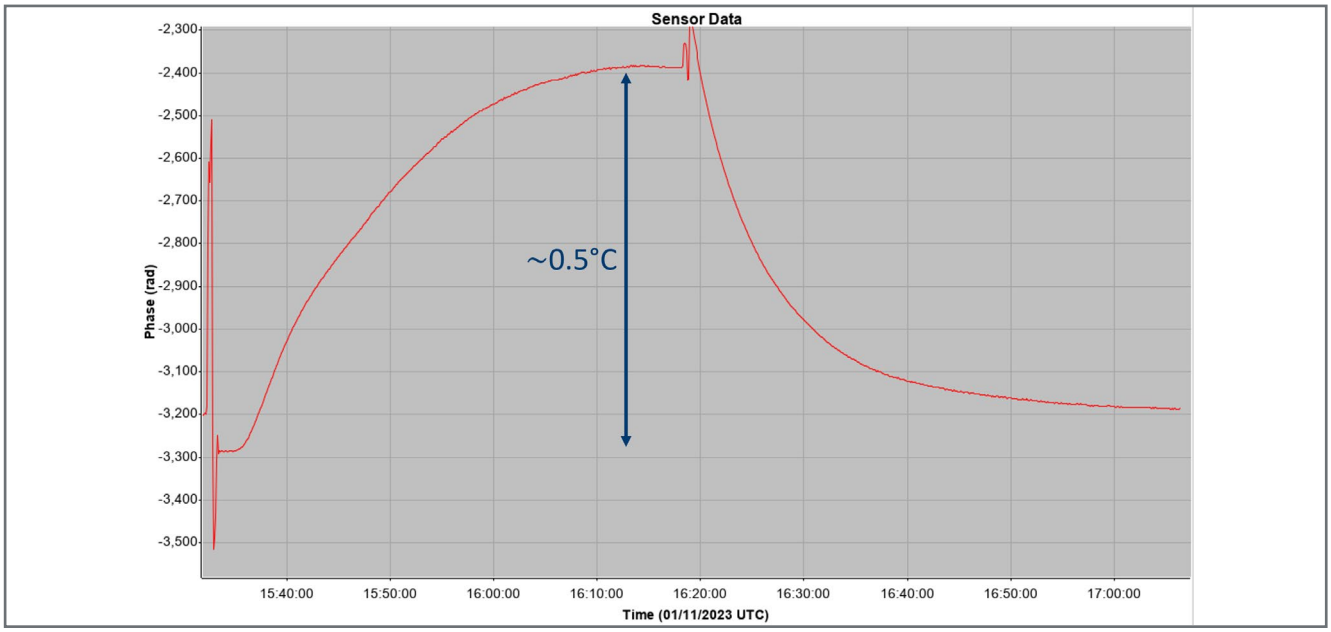

Figure 6: Response of DAS system to the application and removal of a heating element on the ground 0.5 m above the fiber. The observed change in phase corresponds to about 0.5°C.

Typical Pipeline Performance	Sensitivity		Response time		Location Accuracy
	Buried	Above Ground	Typical	Variances	
Liquid Leak NPP	<5 LPM (<2 bbl/hr)		1 min	/	±10m (33 ft)
Liquid Leak (OFN/Strain/DTGS)	150 LPM (57 bbl/hr)	250 LPM (95 bbl/hr)	5 min	1 to 15 min	
Gas Leak NPP	2000 SLPM (71 scfm)		1 min	/	
Gas Leak (OFN/Strain/DTGS)	5000 SLPM (177 scfm)		5 min	1 to 15 min	

Table 1: Typical Pipeline Performance

increased uptake as a leak detection solution. These efforts have been further reflected by the recent updates to the API 1130 and 1175 Recommend Practices where external leak detection methods such as fiber optic sensing are recognised along with other leak detection standards developed by major global oil companies.

4.6 DAS Tuning

With the presence of thousands of sensing channels and the many variables that can impact the signal observed, a question that arises is how a DAS system can be tuned in the field. The base assumption must be that the effect of a leak will generate a signal above that of the background environment. With NPP detection, the large spatial component and distinctive shape allows incredible sensitivity and ease of configuration: the tuneable component is simply the speed of sound in the product, which is generally known or can be easily determined. In contrast, OFN/Strain/DTGS detection is looking for highly localised signals occurring over longer periods of time and that might see similar signals arising from non-leak events.

In the early days of deploying DAS leak detection systems, tuning would involve taking a sample of data – typically 24+ hours – and identifying the typical signals observed over this period. Detection thresholds would then be configured above the maximum signal observed across the system (Figure 7). Different thresholds might be configured for different sections of the pipeline to accommodate changes in environment and while this would improve the thresholding the individual channel sensitivity would be sub-optimal for large sections of the system. Ideally, a threshold would be configured for each channel but to do so would have been completely impractical. Even if thresholds had been configured for each channel, they would still have been set based on the observations made within the period of evaluation.

To address this issue, when OptaSense OS6 was released back in 2021 one of the key features was the use of statistical methods to achieve the desired channel-by-channel configuration. Each channel along the pipeline continuously monitors the local signal variation and uses this information to understand its local environment. Thresholds can then be set relative to this background. As more data is acquired and the system experiences different patterns of life the thresholds will adjust until each channel is as sensitive as possible. This produces a set of thresholds that are uniquely adapted to the local environment for each installation (Figure 8).

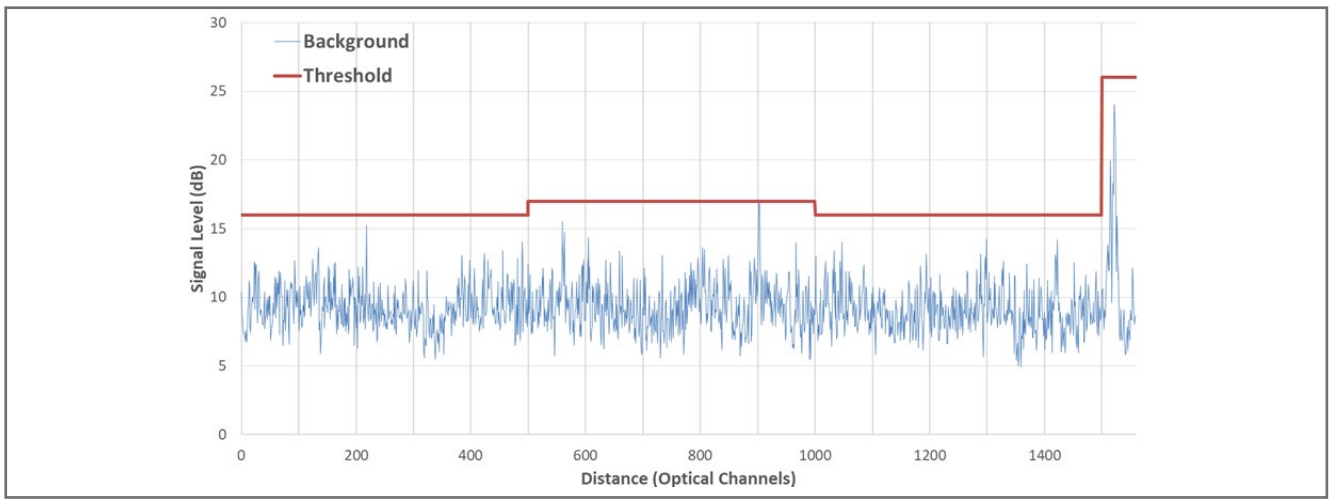

Figure 7: Example of thresholds being set across sections of system based on 48-hour monitoring.

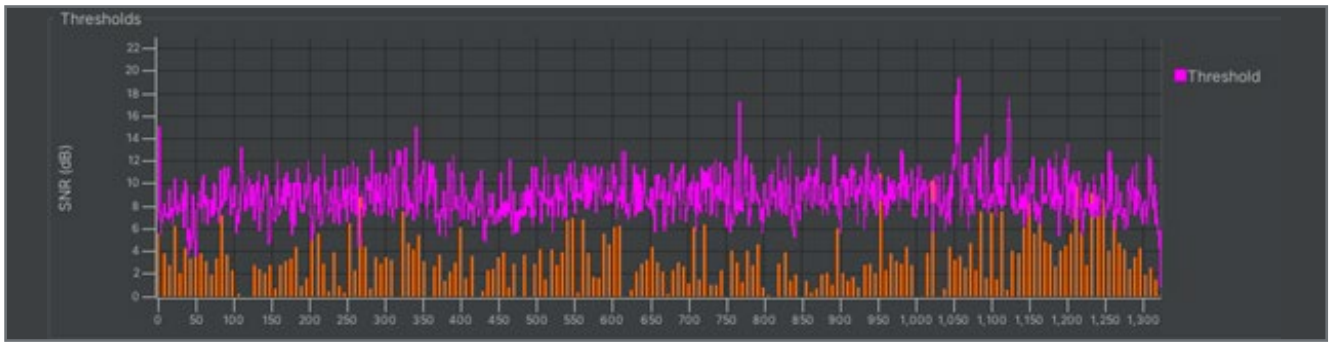

Figure 8: Channel-by-channel thresholding as implemented in OS6.

This doesn't mean that the thresholds will be changing frequently from day-to-day. After sufficient information is available, the background level will be extremely stable and so the thresholds themselves will also change minimally. On top this, if there is a region that has a higher likelihood of producing a leak it is still possible to specify regions to refine the sensitivity.

5. Field Testing

Over the years, many field trials on a variety of scales have taken place for both buried and above ground pipelines. The more representative a test is of a real leak the better and, short of genuine leaks, these proxy tests are always going to be the best way to develop and verify the performance of a system[4,5]. For all the testing that DFOS providers undertake, once a system is configured it stands to reason that the pipeline operator will see on-site validation as desirable. Proxy tests to simulate the effects of a leak are really the only option given the understandable reluctance to cause a real one. Below, several options for testing are discussed in brief[6]. These are intended to be representative of a leak rather than simple system tests, such as alert injection that can be used to validate system integration.

NPP Generation (DAS)

The rapid opening of a valve can be used to simulate the sudden loss of pressure that occurs in a pressurised pipe when a leak begins. Ideally, the event should be triggered by a rupture disc to replicate the instantaneous failure of containment. Tests can take place on an accessible section of the pipeline arrangements to capture escaping fluid can be implemented if required.

Leak Injection Rig (DAS/DTS)

The localised acoustic effects of a leak can be simulated by injecting gas/liquid into the ground at pressures and flow rates commensurate with the expected performance. In doing so, it is possible to replicate the effects of a multitude of leaks at different offsets and orientations from the fiber.

Simulated Thermal Effects (DAS/DTS)

Localised application of appropriate temperature differentials can be used to mimic the thermal effects of a leak. This might be achieved with heated/chilled blankets. The key is that the effect should provide a representative temperature differential and affect a realistic amount section of pipeline for a sustained period. In one instance, a thermal event was generated through the application of a blow torch directly to a section of a test pipe.

Leak Simulation Unit / Fiber Stretchers (DAS)

These devices function in a similar way to a loudspeaker and can be used to apply known signals to sections of fiber. Devices can be spliced in-line or installed at the end of a system. The signal content and amplitude are all adjustable and the aim should be to apply signals that are derived from and represent real leak events rather than simply demonstrating that the presence of a large signal will trigger an alert.

6. Future with ML/AI?

There is no doubt that Machine Learning (ML) and Artificial Intelligence (AI) are hot topics now. Furthermore, it is clear across many industries that these technologies are already showing great promise, such as the rapid detection of microscopic cancers. Across the DFOS industry, many providers are implementing ML and AI technologies. The key consideration is to apply it where there is a realistic prospect of seeing a benefit. We must be mindful not to blindly apply ML and AI just for the sake of it. One of the characteristics of these technologies is the need for large training datasets with which to generate algorithms that can identify

the correct events. However, even with large datasets, the opportunity for problems still exists: One commonly used story to highlight potential failures comes from image classification algorithms failing to distinguish between chihuahuas and muffins.

At LUNA Innovations, an example where ML has been utilised is in the detection and tracking of trains[7]. Here, vast amounts of data containing a variety of train signatures was harnessed to train the algorithm in conjunction with an even greater quantity of data containing no trains and non-train signals. For leak detection, vast amounts of data with no leaks exists but the amount of data available for a range of genuine leaks, across a range of installations, is limited. That isn't to say that ML/AI may not one day be useful for DFOS leak detection but that it may take time for the necessary training data to produce reliable algorithms to become available.

A further, often-undiscussed aspects of developing ML/AI algorithms is the preparation and presentation of data. DFOS can produce vast amounts of data at very high rates that we want to process in real-time. This is not conducive to edge-processing or cloud-processing without significant data conditioning and the risk with any data conditioning is the removal of the very features that allow accurate detection to occur. The ability to understand the physical effects that can occur and consider how it might look in different scenarios is key to knowing how best to present that data to any detection algorithm.

In the long run, ML/AI technologies will almost certainly benefit DFOS systems whether implemented for the purposes of leak detection or not. To maximise this potential, and indeed for general system development, the actual data from real-world systems is invaluable. Obtaining such data relies on a pipeline being monitored, developing a leak, and identifying the leak in a timely manner, all with a system recording the raw data. Even assuming those elements are true, there's no guarantee that the relevant data will be backed up for future reference. So, a plea: If a leak occurs on your pipeline that is monitored by DFOS, whether it is detected or not, please make that data available.

7. Conclusions

The future of Fiber Optic Based Leak Detection is an exciting one for several reasons.

- Greater integration of DAS and DTS to form complementary sensing systems with DTS allowing DAS systems to maintain a thermal stability so that the incredible temperature sensitivity and reaction time of DAS to be utilised for effectively.
- The move to quantitative-DAS sensing as standard will bring a step-change in capability.
- The uptake of FOLDS across the world not only within the Oil and Gas sector but the wider pipeline community will lead to the availability of wider data sets for leaks to refine, update and develop new algorithms.
- ML/AI technologies are likely to benefit other industries first where there are richer datasets with which to develop solutions, but in time will benefit FOLDS for pipelines

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The Future of Risk based Integrity Management using AI Approaches

T.BASTEK, J. SCHMIDT > CSE CENTER OF SAFETY EXCELLENCE

Abstract

Pipeline Integrity Management Systems (PIMS) have significantly improved the safety of pipelines in Europe and the United States. New technologies such as artificial intelligence (AI) and modern Geographic Information System (GIS) visualization can and will elevate pipeline integrity to a new level. However, challenges for pipeline integrity have emerged, including the integration of hydrogen as a new liquid and the impacts of anthropogenic climate change. Risk-based approaches in PIMS are crucial for identifying and mitigating hazards, optimizing inspections, and ensuring technical integrity. AI aids in accurately predicting pipeline safety, while addressing third-party impacts and corrosion rate calculation. The RiIM research project at the CSE Center of Safety Excellence Institute aims to tackle these challenges, making PIMS more systematic and future-proof.

1. Pipeline Integrity Management Systems

Pipeline integrity management systems are powerful tools which have improved safety of pipelines in Europe and in the United States[1,2]. Recent more advanced technologies using the enormous quantity of data available attempt to raise the pipeline integrity on an even higher level. Efficient ways of handling and analyzing data, automated assessments, and clear GIS visualization characterize major opportunities of current PIMS [3]. But there are also emerging challenges. Hydrogen as a new liquid is on the horizon, but operation uncertainties and societal risk concerns about its safety persist, as do incidents in classic natural gas pipelines. Recent particularly public examples of the vulnerability of gas infrastructure in Germany like the flooding in the Ahr Valley caused by heavy rainfall or the attack on the North stream offshore gas pipeline at the bottom of the Baltic Sea have intensified the discussion on pipeline safety. In PIMS process integrity is assessed by analyzing safety and efficiency. Therefore, hazards to which the gas pipeline is subjected to must be identified, recorded, and evaluated. Hazards as described above can hardly be prevented completely, but their probability of occurrence and potential impact can be reduced by appropriate measures. Suitable measures can be of a protective - technical nature, such as the safe design of gas pipelines taking into account the hazardous forces to be expected, but also of an organizational, monitoring nature, such as ILI, CP measurement, patrolling, and metrological monitoring of the gas pipeline and the surrounding area. These measures can be systematically defined and justified by evaluating the risks along the pipeline. Accordingly, a risk-based approach in PIMS is suitable for assessing these hazards to ensure technical integrity.

2. Pipeline Integrity in Germany

Traditionally, pipeline integrity in Germany is maintained through time-based inspections and maintenance. Regular inspections for leak detection and tests are performed at distinct intervals to ensure that the gas pipeline has a proper integrity. While these methods provide general information levels about the pipeline, they have their limitations. It is in many cases expensive and inefficient, since low-risk areas are unnecessary inspected while it is insufficient in high-risk areas, leaving potential events undetected. Further PIMS development is necessary. Globally, the concept of risk-based pipeline integrity management has become established in recent years [4]. This approach focuses on identifying and prioritizing risks along the pipeline and enables operators to target their resources more effectively and efficiently. Instead of rigid schedules, inspections and maintenance work are carried out based on risk assessments. Higher risk areas receive more attention, while less critical areas require less frequent inspections. Risk-based pipeline integrity management doesn't rely solely on manual assessments, however. This is where one of the application areas of AI and digitalization comes into play. With AI technologies, pipeline operators are able to develop models that use pipeline, operational, and environmental data to more accurately and systematically predict pipeline status, enabling them to respond to potential problems earlier and more reliably.

3. Hydrogen,Climate Change & Third Party Impact

New risks caused by hydrogen must be recognized [5]. Hydrogen has never been used at such pressures in these quantities in existing pipeline systems. Experience with conversion of natural gas pipelines to hydrogen is limited, so there is no certainty based on operational experience. The effects of hydrogen on pipelines or the correct operating conditions and components are already being investigated in numerous research projects. This research projects investigate risks and evaluate the potential effects when integrity is lost, and pressurized hydrogen is released. The properties of hydrogen are very different from those of natural gas. Ignition energy, density, operating conditions, emission spectrum and reactivity are just a few examples of differences that influence the risks in operation when repurposing from natural gas to hydrogen.

Furthermore, the impact of anthropogenic climate change as a result of the greenhouse effect is another challenge for the safety of gas pipelines [6]. Climate change means a steady change in the climate due to the emission of greenhouse gases as part of industrialization, and the effects have been occurring more frequently in the recent past. The increasing impacts of climate change, such as more extreme weather events, temperature fluctuations, and increased precipitation, mean new, more intense, or more likely threats to gas

pipeline integrity. Gas pipeline risk analysis must consider climate change as a significant factor. This requires assessing potential climate risks in relation to the geographic location of the pipelines, regional climate, and expected changes over time. The first step is to identify the hazards, derive scenarios, identify influencing factors, and derive the probability or determine impacts to integrity. It is integral that time dependent risks due to climate change are identified, to apply sufficient safety measures at the right time.

Consideration of third-party impacts in risk assessment is a critical step in the Pipeline Integrity Management System (PIMS) process. Impacts caused by third parties occur spontaneously, can be severe such as Oppau, Ludwigshafen 2014, and cannot be excluded due to their diversity and force. Accordingly, risks must be assessed and sufficiently mitigated with appropriate measures. The probability of an integrity loss due to third-party impacts depends on a variety of factors, such as the number of construction sites, the design of the pipeline, the protective measures, but also the construction equipment used. These complex risks can be assessed e.g. using Bayesian networks [7]. In this context, AI can help fitting parameters and creating a model able to predict damages due to third party.

4. AI in the process of State Assessment & Corrosion Rate Calculation

Another promising field is the integration of AI into the process of state assessment / corrosion rate calculation. Classic modeling for corrosion rate calculation is based mostly on empirical experience and expert judgments. It takes into account individual but limited factors such as material composition, individual environmental parameters, protective measures such as coating and CP, or the chemical properties of the transported gas. These experiences are valuable and help to lead to conservative predictions of the change of state in regular corrosion cases. Although this classical method provides important insights as an approximation to real corrosion, it still has limitations. For instance, it may have difficulty accounting for hard-to-capture correlations or variable operating and environmental conditions that significantly affect actual corrosion. This is where AI comes to the rescue. AI models can process large amounts of data from multiple sources and

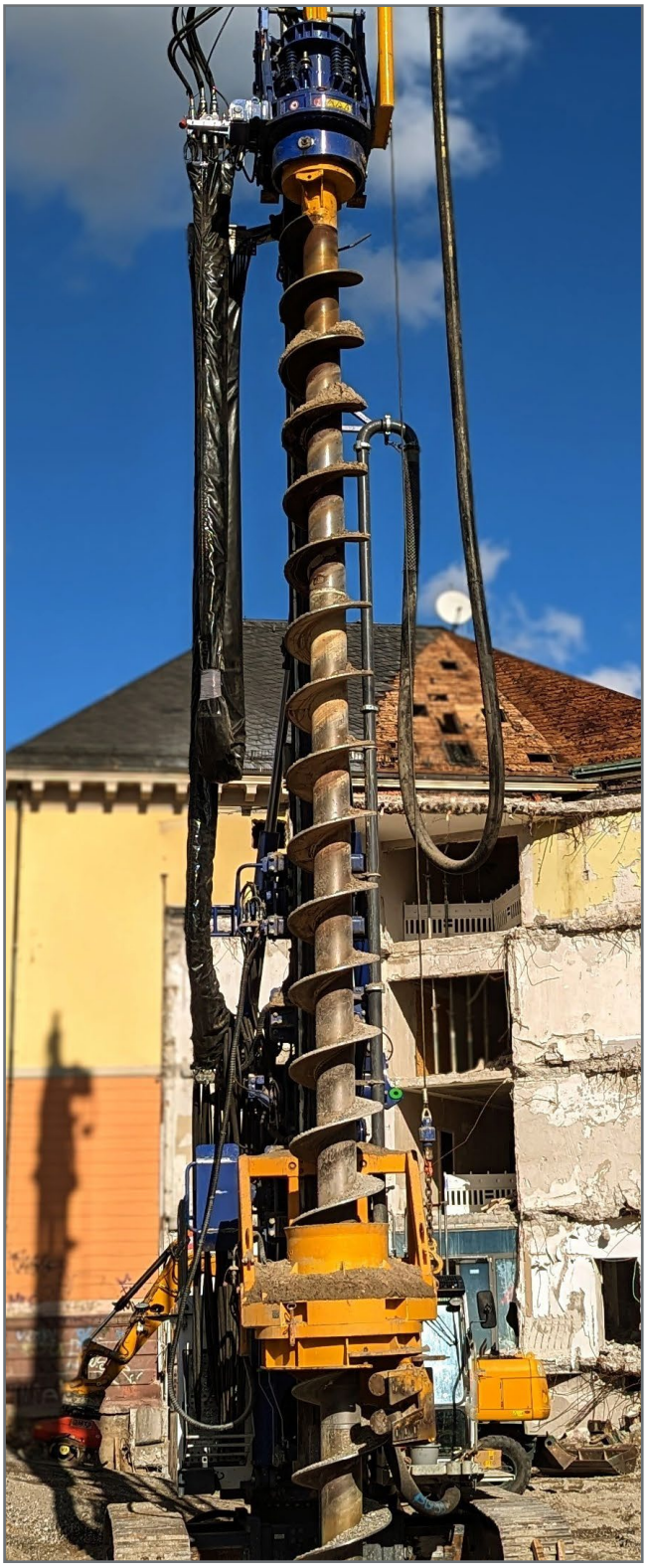

Figure 2: A potential gas line third party hazard - heavy soil auger during civil engineering work at a city construction project.

identify patterns and correlations that are not identifiable to the human eye but still have a relevant impact on corrosion rates. Overall, integrating AI in a hybrid approach to classic corrosion rate calculation on gas pipelines can significantly improve the safety, reliability, and

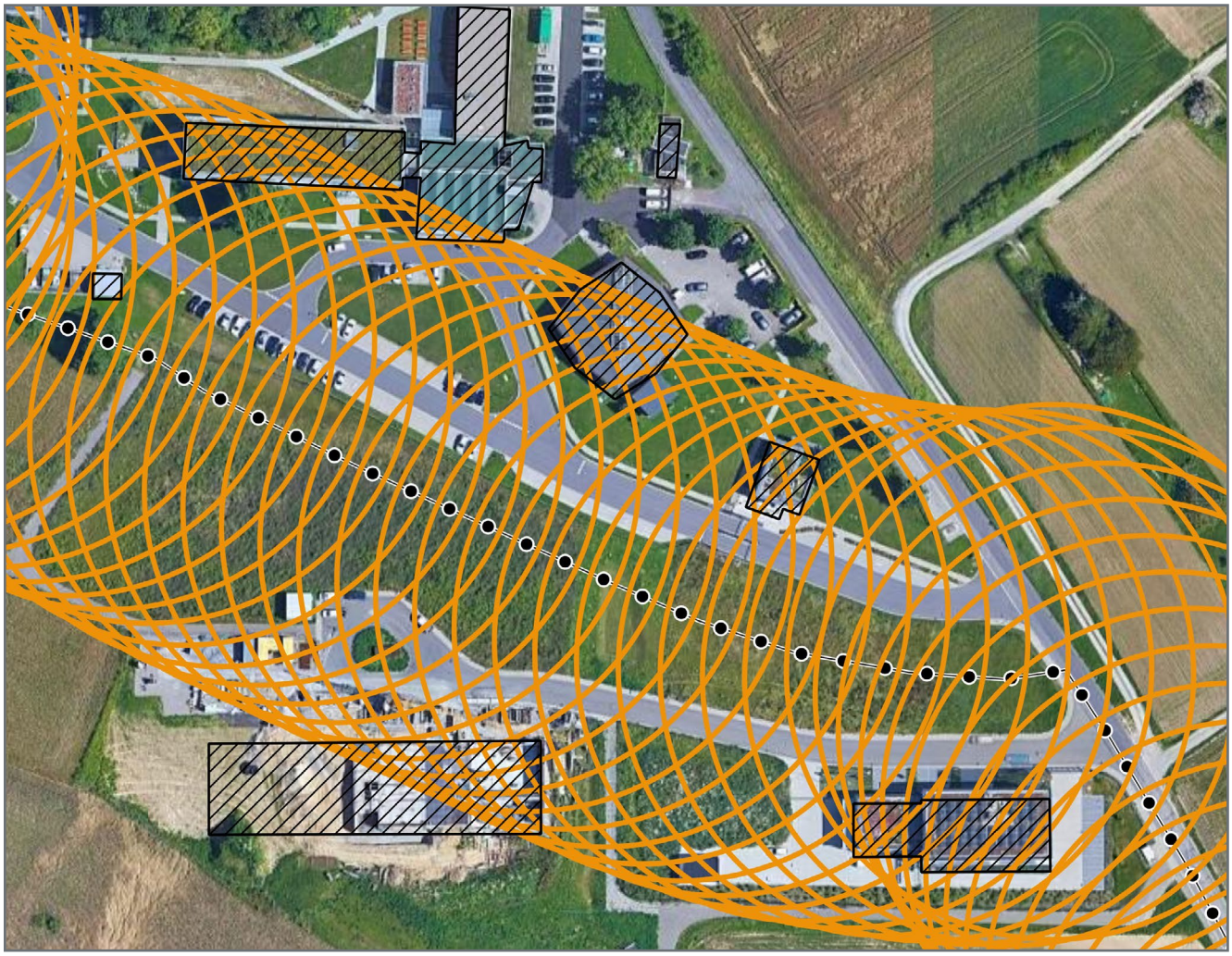

Figure 3: Automated pipeline assessment incorporating environmental and material data through risk analysis.

efficiency of operations. The experience of the classic corrosion model is kept while the AI accounts for factors not recognized and therefore improves the result. It is an example of how the synergy between traditional engineering and modern technology can produce transformative solutions [8]. Hybrid models are also able to bridge the gaps in case of limited data. This has already been demonstrated and tested in another case by the CSE Center of Safety Excellence [9].

5. AI in Pipeline Integrity Management

The integration of AI into pipeline integrity management marks a significant step into the future of this important sector. The previous sections have highlighted the role of AI in risk assessment and prediction of condition changes in gas pipelines. A look at the technology and current developments shows the tremendous potential of this approach and how it will change the way pipelines are managed. AI enables more accurate identification and prioritization of vulnerable pipeline sections, leading to more targeted use of inspection and maintenance. Preventive measures can avoid unnecessary repairs and downtime while improving safety. Furthermore, AI models can be continuously optimized and trained on new data. This enables continuous improvement in risk assessment and integrity management over time. While there are undoubtedly many benefits to integrating AI in pipeline integrity management, there are also some challenges and concerns to consider. Sensitive data must be kept secure, errors and inaccuracies in a model must be accounted for, and further refinements must be performed by experts.

6. Risk-based Integrity Management (RiIM)

The Risk-based Integrity Management (RiIM) research project at the CSE Center of Safety Excellence breaks new ground in integrity management. Hazards, that are not ruled out by countermeasures, are assessed in

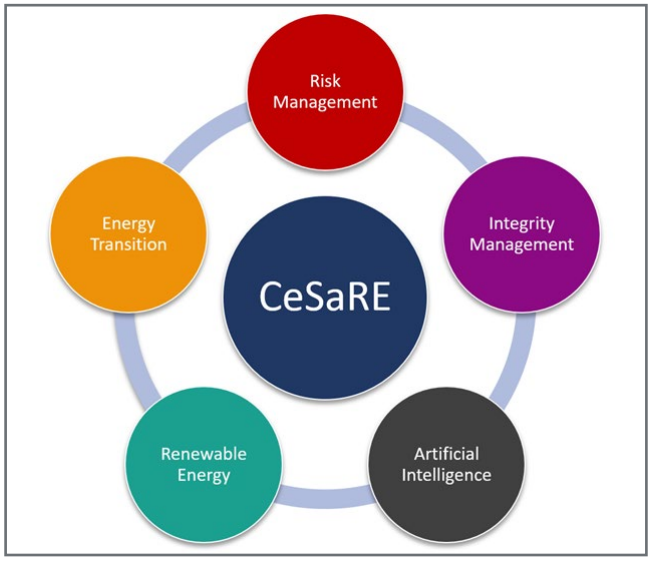

Figure 4: The research project: „Risk-based Integrity Management"(RiIM) is part of the „Center of Safety of Renewable Energies"(CeSaRE) at CSE institute. It integrates the current emerging Safety-Issues due to Climate Change and Renewable Energy with the current methodologies in Risk and Integrity Management.

the form of risks. 1) Risks due to pipeline repurposing to hydrogen are investigated, 2) new hazard scenarios induced by climate changes are taken into account, 3) third-party impacts are determined specifically to certain pipeline sections, and 4) the condition assessment is extended by an AI hybrid approach. As a result, PIMS is expected to leap forward, provide a more systematic and traceable integrity assertion, and apply measures in the right place to reduce costs while increasing safety. It is also important to make PIMS future-proof by integrating already identifiable changes, such as H2 repurposing of pipelines and the effects of climate change, at an early stage.

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