Beyond Compliance: Optimization Opportunities of the Gas Mega Rule – Pipeline Integrity Management with Digital Twins, Multiple Inspections, and Artificial Intelligence

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Executive Summary

As pipeline integrity management evolves with technology, integrating predictive Causal Artificial Intelligence (AI) modelling with real-world simulations becomes a compelling tool for the modern pipeline integrity engineer. This paper explores the synergy between modern digital twin technology and Causal AI-driven enhancements, demonstrating their potential to optimize regulatory compliance opportunities while streamlining threat and risk management. By exploring the integration of these technologies, pipeline operators not only achieve regulatory compliance but also set the stage for a new era of predictive maintenance, operational resilience, and long-term sustainability in pipeline integrity management.

Abstract

The Gas Mega Rule not only imposes stringent requirements on pipeline operators, but also provides an opportunity to streamline integrity management practices through gained efficiencies. By integrating digital twins, AI-driven compliance solutions, and data from multiple inline inspection (ILI) runs, operators can move beyond regulatory compliance while enhancing pipeline safety and operational efficiency.

Digital twins act as virtual models of pipeline systems. These models enable predictive analytics, allowing operators to simulate risk conditions like corrosion and stress, and prioritize maintenance and inspections where needed. This proactive approach reduces unnecessary work and targets integrity management funds to high-risk areas, maximizing safety while minimizing costs.

Multiple ILI runs, using technologies like magnetic flux leakage and ultrasonic testing, generate vast datasets that can be consolidated to provide a clear view of pipeline conditions. When strategically analysed in a digital twin environment, this streamlines decision-making, reduces downtime, and optimizes repairs, extending pipeline life and cutting maintenance costs. With AI integration, operators can automate data processing, anomaly detection, and regulatory reporting, meeting Mega Rule compliance while improving efficiency. AI also helps predict corrosion growth, optimize inspection intervals and chemical programs, improve integrity assessments even when not all data is available, and reduce human error, allowing engineers to focus on high-value tasks.

By integrating AI compliance tools with digital twins and ILI data, operators can turn compliance into a strategic advantage. AI-driven insights, such as using AI to predict corrosion growth and mitigate microbial-influenced corrosion (MIC), enable faster, more accurate decision-making and pre-emptive maintenance actions, improving safety and reducing operational costs along the regulatory compliance path.

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Digital Twins – The Foundation

Digital Twins are generally understood as a digital model of a real-world system used for simulation purposes. For this discussion, we are looking at an existing pipeline or pipeline system with known physical characteristics in an environment with dynamic surroundings. Two common digital twin examples are pipelines in Geographic Information Systems (GIS) and risk assessment databases.

Various types of digital twins serve as the backbone for modern pipeline integrity management, transforming vast datasets into actionable insights. The digital twin integrates known physical characteristics with dynamic environmental and operational data, creating a powerful tool for predictive analysis and optimization.

The gas pipeline industry's efforts to meet the stringent requirements of the Gas Mega Rule has led to the creation of expansive datasets, including detailed pipeline properties, historical inline inspection (ILI) and pressure testing data, other inspection data, and geospatial information. These datasets now enable operators to construct comprehensive digital twins that dynamically reflect the state of their pipeline systems. Similar to standard risk and threat assessment data, some examples of digital twin model inputs include the following.

- **Pipeline Characteristics**
    - Detailed pipeline location, material, and construction data (e.g., vintage, grade, wall thickness, manufacturer, seam type)
    - Pressure test data - commissioning and integrity management program pressure tests
- **Inspection Data**
    - ILI data - both indications and Inertial Mapping Unit (IMU) results
    - Susceptibility analyses for SCC, cracking, seam weld toughness, and other threats
- **Geospatial and Environmental Data**
    - Dynamic and predictive geohazard modeling of the pipeline right of way and surroundings.
    - Integration of lidar, satellite imagery, and seismic data to assess potential risks.
- **Advanced Analytical Tools**
    - Finite Element Analyses (FEA) for modeling stresses and predicting failure scenarios.
    - AI-enhanced simulations to evaluate corrosion growth and operational threats.

Combining these and other operator-specific elements into a robust digital twin model, we gain the ability to perform a comprehensive threat assessment using data on a regional, local, and feature-specific level. For instance, some operators have used digital twins to dynamically investigate MAOP

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values on all pressure containing features within their pipeline system, thereby reducing operational risk and ensuring regulatory compliance with certain parts of the Mega Rule.

Through advanced data validation and QA/QC processes, digital twins provide operators with a platform to address critical challenges. For example, several leading operators use digital twins to assess geohazard threat levels based on real-time geohazard data, significantly reducing operational risks. This approach allows the operator to avoid costly shutdowns and unplanned maintenance, demonstrating the practical benefits of digital twins in compliance and risk management.
By leveraging predictive models, operators can simulate future pipeline conditions, such as corrosion growth or geohazard impacts, and prioritize high-risk segments for inspection or remediation. This proactive approach enables operators to allocate resources more effectively, ensuring both safety and cost-efficiency.

This synergy between digital twins and AI ensures that pipeline operators not only meet compliance requirements but also gain a competitive advantage in cost management and operational efficiency.

Inline Inspection and Current Opportunities

Pipeline integrity management is about understanding and managing risk. As we know, risk is the product of probability and consequence. Inevitably, the probability of failure after early life manufacturing and construction related issues are resolved increases with time as degradation progresses and changes in the internal (operating) and external environment occur. Inline inspection or ILI is the gold standard for assessing the extent of degradation. Hydrotest and direct assessment are valuable tools but have weaknesses. Although important tools, hydrotest won't provide a warning of an impending leak and direct assessment requires a perfect understanding of the degradation mechanisms present to be effective.

ILI is important but not fool proof. Use requires and understanding of what to look for whether corrosion, cracks, clusters of cracks and their orientation, or dents, their associated degradation mechanisms, and an understanding of the capability of the tools in terms of probability of detection and tolerances.

Principle technologies are magnetic flux leakage or MFL which detects volumetric loss, ultrasonic which directly measures wall thickness and callipers which measure the pipelines inside profile. There are variations of the first two, where the orientation of the magnetization or in sonification is varied to focus on a particular defect type. Ultrasonic devices have increased accuracy but require a liquid couplant, practical challenge for gas lines. Electro Magnetic Acoustic Transducer or EMAT is an emerging technology that uses magnetization to generate sound and ensonify the pipeline without

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the use of a couplant. Multiple technologies can be combined into a single run, proving the pig launching and receiving devices can accommodate the length.

One set of ILI results will of course be useful, since, if applied and interpreted correctly will provide a picture of the current condition, or state of degradation. However, a single dataset cannot reliably estimate degradation rates over time. By aligning data from multiple ILI runs, operators can calculate upper and lower bounds for corrosion growth rates and establish credible trends. This enables better repair planning, enhanced confidence in risk assessments, and a clearer picture of the pipeline's remaining life.

Typically, multiple sets of ILI results are aligned, the same features in each set identified and a distribution or upper and lower bound degradation rates identified. This can be used to define an appropriate corrosion rate and associated confidence level. This data can then be used to predict the level of repairs anticipated in the future and the time when these, when compared with the revenue derived from the asset become impractical. This minus the current date is the effect remaining life. Ideally this would be a reasonable time after the pipeline is no longer required. In practice this isn’t always the case, which may require a de-rating or repair strategy to extend the life of the asset.

In any case understanding this will support any decision and minimize unplanned downtime, because intervention can be optimally planned.

Inline inspection (ILI) technologies generate extensive datasets that provide valuable insights into pipeline conditions. However, the sheer volume and complexity of this data present significant challenges for operators. Without effective data integration and analysis strategies, much of the actionable intelligence within these datasets remains underutilized. Advanced data management frameworks, including digital twins, enable operators to consolidate and analyze diverse datasets, turning raw data from various sources into a foundation for informed decision-making.

Additional Data Types

In addition to ILI data, overlaying and integrating other types of surveys, field, environmental, operating, inspection, materials, and manufacturing data can also be very important in obtaining and acting on insights. Both in 49 CFR §192 Subpart O and The Mega Rule, the Pipeline and Hazardous Materials Safety Administration (PHMSA) calls for data integration and analysis of interrelationships to understand threats. For example, overlaying the profile with the location of internal corrosion can be used to diagnose water dropout and associated corrosion, and corrosion at high points in gas condensate systems can be used to identify top-of-line corrosion. Superimposing DC voltage gradient (DCVG) and external corrosion features can be used to determine active corrosion at coating defects, and associating these with top-of-the-line dents can indicate third-party interference. Likewise, the

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proximity of powerlines, solar farms, other pipelines or infrastructure will provide insights into future problems and allow time to plan for mitigating measures. The integration of satellite imagery can provide an early warning of encroachment on a right of way, and lidar imagery combined with seismic data and IMU data can be used to detect ground movement and the development of potentially injurious bending strains that could coincide with wall loss due to corrosion.

Multiple and disparate data type integration, spatial orientation, visualization, and assessment are ideally suited to software that can quickly ingest, align, map, graph and assess data by building and maintaining a digital twin. The integrity engineer can use such tools to schedule additional surveillance, protection, investigatory digs, repairs, and changes in operating conditions, as well as to liaison with landowners and track them with intuitive key performance indicators.

Data Management and Integration

Data and data management is a cornerstone of modern pipeline integrity strategies, yet it presents unique challenges and significant opportunities. The vast volumes of data generated by ILI, coupled with material property, initial construction, pressure testing, and periodic inspection data require effective consolidation and interpretation. Data integration challenges present opportunities to deploy tools that harmonize diverse datasets, enabling seamless alignment and analysis.

Challenges in Data Management

- **Data Integration:** Bringing together disparate datasets from multiple sources and formats into a cohesive system.
- **Data Quality**: Ensuring accuracy, consistency, and completeness of data to support critical decision-making.
- **Resource Constraints**: Managing the computational and human resources needed for advanced analytics.

Opportunities for Advanced Analytics and AI

- **Unified Systems of Record**: Developing centralized databases, such as digital twins, to provide a single source of truth for all pipeline data.
- **Predictive Analytics**: Leveraging machine learning to identify patterns and anticipate potential threats.
- **Enhanced Decision-Making**: Using advanced analytics tools to transform raw data into actionable insights, improving both safety and efficiency.

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- **Increasing Fidelity –** Reducing granularity of data for threats such as geohazards and outside force threats

By addressing these challenges and harnessing opportunities, operators can align their data management strategies with Mega Rule compliance timelines, ensuring proactive threat identification, efficient resource allocation, and ultimately improved pipeline safety.

Mega Rule Compliance Timing Opportunities

On the surface, when considering the requirements of the Gas Mega Rule, we see stringent requirements that mandate data management, inspection, and remediation activities that ultimately cost money to implement. That said, if we take a step back and look at the overall long-term viability of keeping pipeline assets in service as petroleum and gas volumes continue to grow[1], the Mega Rule presents an opportunity for the pipeline industry to adopt a forward-looking approach to compliance, extending to 2035 and beyond. Anchored in stringent requirements for Maximum Allowable Operating Pressure (MAOP) reconfirmation and material property validation, the rule seeks to enhance safety and operational reliability. Adherence to these mandates not only ensures regulatory compliance but also will drive innovations that strengthen pipeline integrity management.

The Gas Mega Rule mandates a phased compliance strategy:

- **2021**: Develop plans for MAOP verification and MCA identification.
- **2028**: Complete 50% of MAOP verification.
- **2035**: Achieve 100% MAOP verification and implement ongoing MCA assessments.

These phased deadlines provide operators with a structured opportunity to deploy advanced tools incrementally. For instance, operators can focus on foundational data validation and digital twin implementation during the earlier phases, then integrate predictive analytics and AI-driven solutions as they move toward full compliance by 2035.

Nearing the 50% deadline, industry has made strides in meeting Mega Rule requirements, with a focus on data integrity and traditional engineering / decision making practices. We have also seen rapid adoption of non-destructive material testing technologies as well as innovative sensor development for both direct assessment and inline inspection. These not only give us a clearer look into the integrity and makeup of our pipeline system, but also result in ***large datasets that do not have to exist in isolation.***

If we look to the future, predictive analytics and advanced technologies likely will become more and more important to fully meet the requirements of 2035. If we look at adoption and enhancements

[1] Source: US Energy Information Administration 2024

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in granularity and quality of non-destructive testing, inline inspection, and environmental monitoring data in recent years, we clearly see that it also provides a runway for the rollout of tools, technologies, and techniques that advance over time. We see these showcased in industry literature and case studies at conferences such as PPIM and ASME's International Pipeline Conference (IPCE). By leveraging these technologies alongside the compliance timeline, operators can enhance resource allocation, minimize unplanned downtime, and build scalable systems that adapt to future regulatory changes. This ensures compliance is not only achieved but becomes a driver of operational efficiency.

This inspection and operational data all sits alongside enhancements opportunities to existing data. One such example, which introduces the concept of a "***Master Pipeline Listing***," outlines a methodology to assess and enhance the accuracy of inertial measurement unit (IMU) surveys in pipeline inspections.[2] The approach outlined focuses on identifying and correcting errors from odometers, gyroscope biases, and GPS tie points. The proposed Master Pipeline Listing integrates data from multiple surveys to improve accuracy, reduce redundant GPS surveys, and streamline future inline inspections (ILI). By creating a consolidated, perpetually updated record of pipeline characteristics and inspection data, the Master Pipeline Listing acts as a foundational element of the MAOP Reconfirmation System of Record. This comprehensive system aligns with Mega Rule compliance workflows, enabling operators to address both immediate regulatory requirements and long-term pipeline integrity challenges. Case studies presented in the paper highlight cost savings and operational efficiency, emphasizing the value of accurate mapping for dig locating, anomaly reporting, and pipeline integrity management. This data of course can be used to enhance our Digital Twin of the pipeline system, which we will refer to as our "***MAOP Reconfirmation System of Record"***.

Taking a step further, if we combine these digital twins with Causal AI, we see an opportunity to enhance traditional pipeline integrity practices with new decision-making processes to ensure pipeline system integrity. Meshing data from existing sources into models that are guided by physics, time-delayed cause and effect, and SME knowledge creates a tool that can go beyond standard approximations of pipeline integrity issues and remaining life. An AI model that considers the specific characteristics and impacts of a pipeline's operational environment can provide more dependable insights into areas needing further examination while avoiding unnecessary digs. One of the key features of causal models is that if they do not understand a cause they will not necessarily produce a prediction. This means that causal AI can highlight where it does not have a good answer and help integrity engineers to narrow down the areas they need to focus on. Causal AI models are also more explainable than traditional correlation-based models, making it easier for pipeline integrity engineers to assess the AI's inferences.

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[2]Czyz, J. A., et al. 2024. *Reducing cost of ILI inspections by assessing and improving accuracy of past inertial surveys*. International Pipeline Conference (IPC) Conference Calgary, September 23-27, 2024.

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Engineering Critical Assessments (ECAs) for Integrity Validation and Mega Rule Compliance

Reconfirming MAOP is central to the Gas Mega Rule, with 49 CFR §192.624 detailing methodologies ranging from replacement to pressure testing to Engineering Critical Assessments (ECAs). For pipelines lacking compliant historical documentation, derating poses significant operational and financial challenges. As a result, operators are encouraged to leverage alternative technologies and ECA methodologies. These approaches offer cost-effective solutions while maintaining the integrity of aging infrastructure.

Engineering Critical Assessments (ECAs) play a crucial role in evaluating the integrity of pipeline segments and determining their maximum allowable operating pressures. 49 CFR §192.632 outlines the requirements for conducting ECAs, including thorough analyses of threats, material properties, and defect interactions. Industry trends[3] show us that operators likely need to develop a system supporting effective execution of ECAs activities.

ECAs provide a rigorous framework for assessing pipeline defects, material properties, and failure risks. Governed by the regulation, ECAs allow operators to establish precise MAOP levels by integrating:

- Material Property Data: Comprehensive documentation of pipeline characteristics, such as diameter, wall thickness, seam type, and grade.
- Inline Inspection (ILI) Results: Data-driven insights into pipeline conditions, enabling a detailed analysis of defect interactions.
- Geographic Information Systems (GIS): Spatial context for defects and threats, facilitating targeted remediation and monitoring strategies.

By integrating the data, such a system enables operators to assess the nature of defects and conditions accurately and establish MAOP values for the pipeline system.

In addition, software tools with advanced analytics capabilities allow operators to estimate the remaining life of pipelines containing or susceptible to certain defects, ensuring long-term integrity and compliance. In addition, chosen software solutions should support analysis supporting "Alternative Technology" as outlined in 49 CFR §192.624(c)(6).

[3]U.S. Pipeline and Hazardous Materials Safety Administration. *Annual Gas Transmission & Gathering Data: 2010–Present*. U.S. Department of Transportation, n.d. https://www.phmsa.dot.gov/sites/phmsa.dot.gov/files/data_statistics/pipeline/annual_gas_transmission_gathering_2010_present.zip. Accessed November 25, 2024.

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We see that the incorporation of digital twins and AI-driven tools enhances the execution of ECA methodologies. These technologies create a dynamic digital representation of pipeline assets, enabling operators to model threats, predict corrosion growth, and optimize maintenance schedules. By combining real-time data with predictive analytics, operators can streamline compliance while improving operational efficiency. An example of the MAOP Reconfirmation System of Record and interactions with various parts of Mega Rule compliance activities is presented below in **Figure 1**.

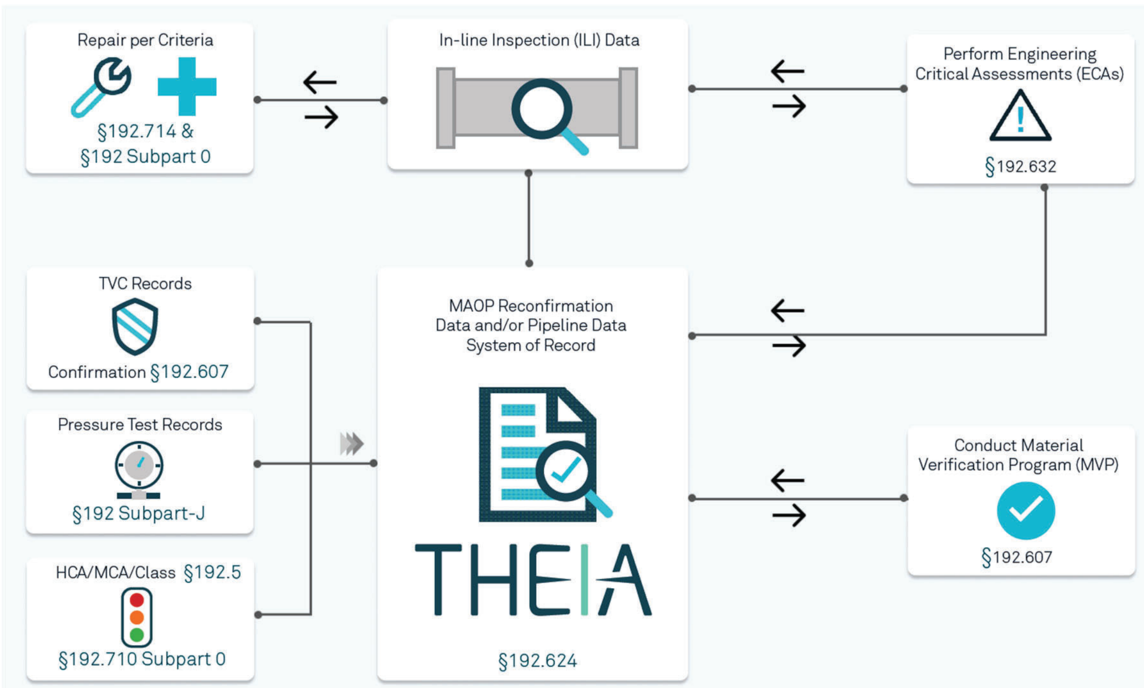

Figure 1. MAOP Reconfirmation System of Record and example Mega Rule compliance workflow

Data and Decision Making

Merging these large ILI and operational datasets into causal AI models has the potential to help operators improve their understanding or corrosion growth changes in between ILI runs, allowing the operators to make informed decisions about when an ILI run may need to occur earlier than originally planned or can be delayed based on the effectiveness of corrosion mitigation efforts. In concert with AI, corrosion experts can use this information for ILI tool selection, moving to more advanced tools in pipelines where corrosion is escalating and using more basic ILI tools where corrosion appears to be well under control. Furthermore, operators can make better use of their engineering resources by guiding them to the areas that need more in-depth analysis that only human SME's can provide.

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A key component of a rigorous integrity management approach is that repeatable Artificial Intelligence (AI) technologies will assist the operator in performing these ECAs, which we detail further below.

Predictive Analytics and Artificial Intelligence

Predictive analytics, powered by AI, is transforming the way operators address pipeline threats. By leveraging historical and real-time data, predictive models can anticipate corrosion growth, detect geohazard interactions, and optimize maintenance schedules. One such advanced tool is Causal AI, a methodology that enhances predictive capabilities by focusing on cause-and-effect relationships rather than relying solely on correlations. The integration of machine learning algorithms into pipeline integrity management enables the identification of patterns and trends that may not be immediately apparent through traditional analysis. The development of predictive frameworks supports operators in managing resource allocation and reducing the likelihood of unexpected failures. For example, predictive analytics combined with multiple ILI runs helps establish reliable degradation rates, improving confidence in future repair planning and risk assessments.

Senslytics' CausX AI platform is a leading example of this approach. Unlike traditional machine learning methods, which often focus on statistical correlations, Causal AI emphasizes understanding the cause-and-effect relationships between variables. This allows it to generate more explainable predictions and actionable insights, even in complex systems with limited data. In the realm of machine-learning correlation-based models, outliers are ignored, and singular activation functions are fine-tuned to fit the data by reducing variance between an estimation and the corresponding ground truth at every step. In contrast, CausX AI does not base its estimation on a singular activation function. Using situational proximity as the threshold, multiple situational clusters are formed from the ground truth data that are then connected to the neighborhood clusters generating multiple situation-specific initial guardrails. For pipeline integrity, this means more reliable predictions for corrosion growth, geohazard risks, and maintenance prioritization, as examples, even in cases where traditional models struggle to make accurate forecasts. These guardrails follow the constraints, patterns, or trends that are derived from the experts' hypotheses which maps the experts' general expectation of the system behavior a given situation. **Figure 2** explains the approach. Unlike one activation function shown on the left in classical ML, CausX AI shows multiple clusters of situations forming multiple guardrails, some mapping the outliers. These initial guardrails are perfected with time as more and more diverse situational data are run through the AI. Situational guardrails are used for estimating system behavior. Depending upon the proximity of the new situation in the background of experience, a ballparking methodology can be applied. Alternately the situational guardrails are translated or extended when the stability of the situational surface supports such operations.

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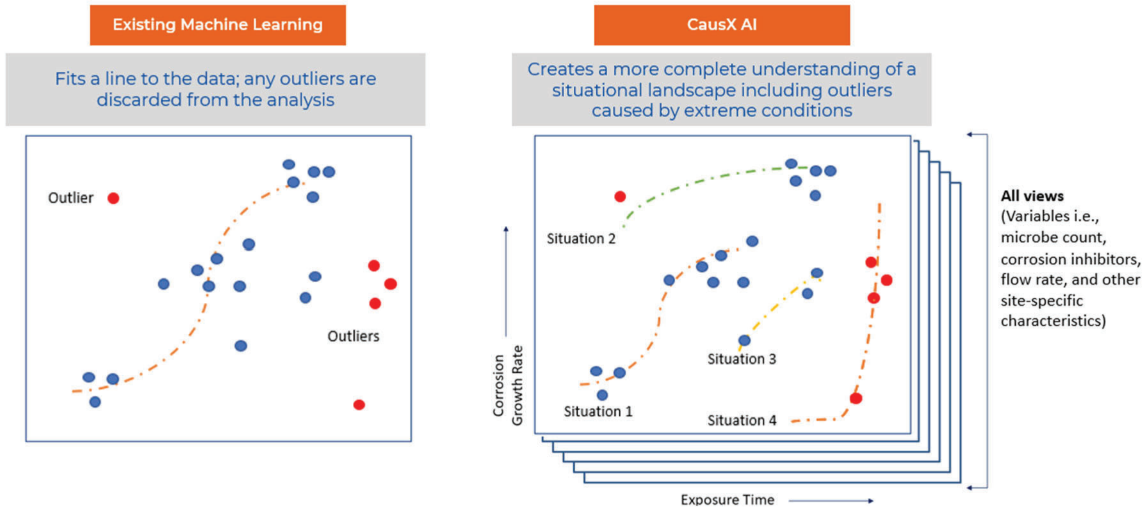

Figure 2. How CausX AI Works

Data and Analytics for Addressing Corrosion Threats

Corrosion remains one of the most critical threats to pipeline integrity, requiring innovative approaches to detection and management. The integration of digital twins with advanced AI tools allows operators to model corrosion mechanisms more accurately, predict growth rates, and identify vulnerable pipeline segments. Techniques such as 3D modelling of corrosion clusters enable operators to forecast failure risks and prioritize maintenance efforts effectively.

One such idea was presented at IPC 2024 and introduced a novel 3D corrosion growth modelling methodology, which incorporates depth, length, and width growth while accounting for interactions between adjacent corrosion sites and new defect initiation[4]. By leveraging machine learning and probabilistic growth rate simulations, this approach addresses limitations in traditional fixed-growth-rate methods. Validation through case studies demonstrates the methodology's effectiveness in accurately predicting future corrosion severity and optimizing inspection and repair schedules. This provides a safer, resource-efficient framework for pipeline integrity management.

The use of causal inference models, such as those offered by Senslytics, has enhanced the ability to detect rare phenomena like microbial influenced corrosion (MIC). These models provide situational awareness and optimize inline inspection (ILI) data to refine corrosion mitigation strategies, ensuring long-term pipeline health.

[4]Dawson, Jane and Steve Farnie. *Accounting for Corrosion Growth and Interaction*. International Pipeline Conference (IPC) Conference Calgary, September 23-27, 2024.

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Case Study - Identifying MIC

Corrosion influenced by microbes often catches the pipeline operators off-guard and is possibly the least understood form of corrosion. Few inherent characteristics of microbes make MIC modeling so challenging. In fact, the assumptions, and underlying premises upon which machine learning (ML) models are constructed today might never fully capture the intricate dynamics of MIC growth in a definitive way. Some of those challenges are as follows.

- Microorganisms can remain dormant for a long time if the environment is not suitable for growth. ML suffers in modeling time delayed effect when the delay fluctuates significantly with the changes in situation.
- Microbes can grow exponentially, displaying sudden extremities. ML models discard these extremities as outliers prior to modeling the data.
- Microorganisms function on a microscopic scale, and much of their activity remains invisible at the macroscopic level, leaving ML unaware until it is too late. This makes especially the supervised learning models ineffective where real-time feedback of the output is necessary.
- MIC growth can exhibit significant variations based on the presence of specific inorganic and organic chemicals in the microbial environment. These compounds play a role in sedimentation and catalyzing reactions. However, traditional machine learning struggles to model such influential factors that lack direct correlation with the output.

An example result is presented here. CausX AI was applied to detect internal corrosion growth areas on a pipeline approximately 68 miles long. Only two ILI reports from 2005 and 2010 were analyzed to predict vulnerable areas of the pipeline and identify MIC-affected regions. A report from the pipeline operator from 2010 that includes a lab analysis of one section of the pipeline confirms the presence of microbes and MIC in that region. This section was among the stretches identified by the AI model as having critical levels of corrosion growth. By leveraging the corrosion signature observed in this MIC-confirmed region, the model further identified other regions likely to have been affected by MIC. This analysis was done using only ILI data. CIS and operational data could further enhance this analysis.

Error! Reference source not found.Figure 3 shows the outputs of the CausX AI model after analyzing ILI data from 2005 and 2010. The first image depicts the AI model's criticality projection across the pipeline, where a criticality level of 0 indicates no issues, and a level of 5 highlights pressing concerns, including the need for near-term repairs. The second image shows the AI model's identification of MIC-affected regions (shown in dark red) based on the learned corrosion signature. The circled region represents the only point of ground truth, where MIC-related issues were confirmed.

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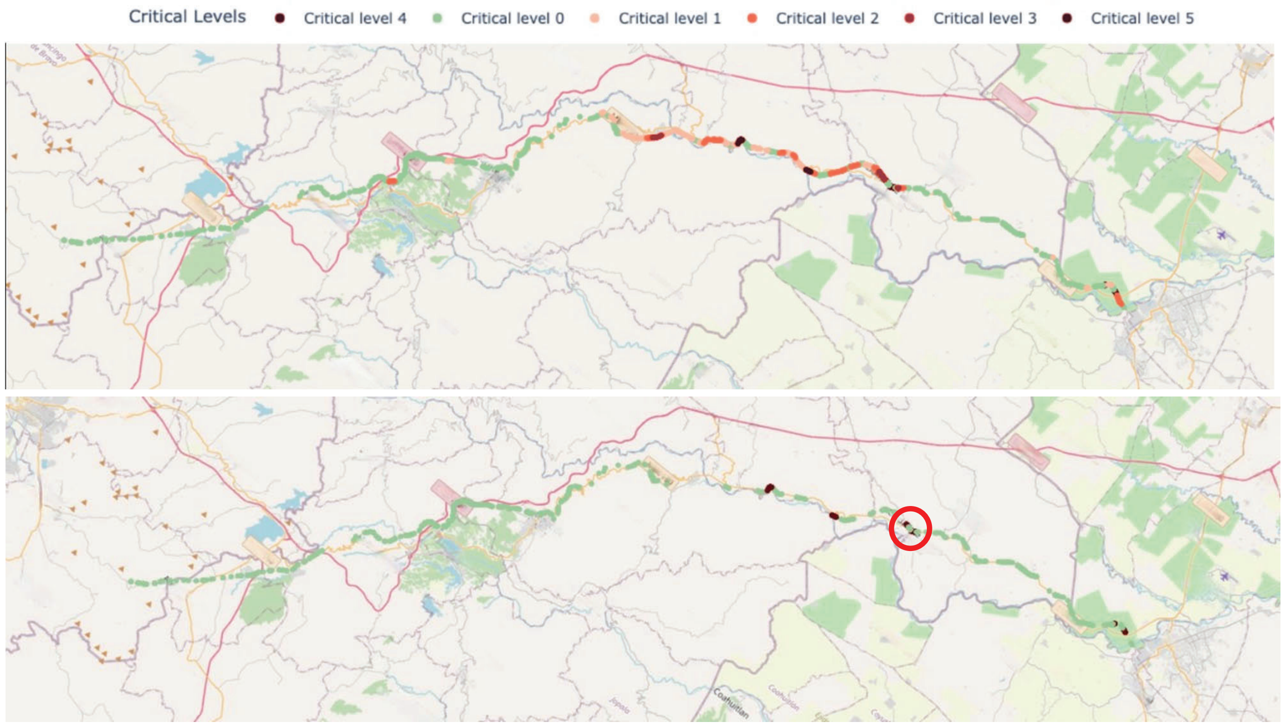

Figure 3. ILI Runs to Forewarn Critical Corrosion

CausX AI takes two intriguing approaches to detect the potential internal MIC growth areas in a long pipeline.

1. Anomalous corrosion growth detection: Corrosion mechanism is different between the galvanic and microbial. Microbial corrosion is a result of the survival attempts of microbes through forming and expanding biofilms as protection shield first and then thriving from it as situation becomes favorable. As shown in **Figure 4** microbial colonies grow by taking an anisotropic shape because it harnesses the advantage of the path of most survival favorability, like how ancient human cities expanded along a riverside. Galvanic corrosion has no compelling reasons to display anisotropic growth.

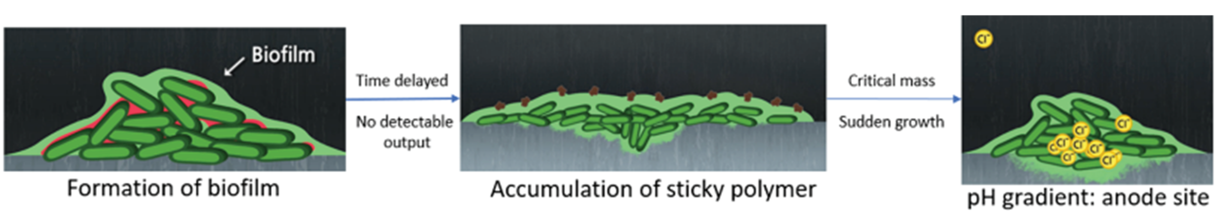

Figure 4. MIC Growth Process

MIC also shows sudden growth when the situations become congenial, therefore a sublinear to exponential growth pattern is expected in MIC areas. In fact, this happens because the MIC aids the galvanic corrosion by creating a positive feedback mechanism for corrosion growth as

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displayed in Figure 5. It is important to note that microbe count in the fluid has no scientific correlation with microbial corrosion. The pre-requisite for MIC is the attachment of the microbes to the surface of the pipeline and settling in.

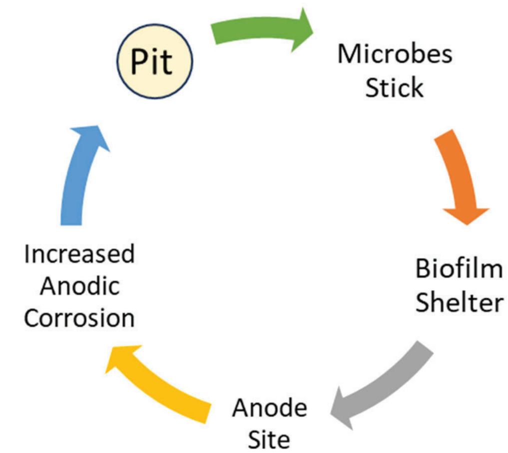

Figure 5. MIC and Galvanic Corrosion Symbiosis

2. Recursive zooming in and magnify: Spotting areas of MIC growth in miles and miles long pipeline is easy. The proprietary recursive zooming feature of CausX AI becomes helpful. The AI divides the pipelines into 100 segments and finds the clusters of anomalies and zooms into those segments only, divining them into a further 100 segments. This process continues till the window is in 12-15 feet range. At every zoom-in and magnify iteration, the top percentile spots are chosen from each Corrosion view.

CausX AI takes into account various views e.g., feature growth, metal loss, growth anisotropy, clock position etc. to consistently coincide with each other for determining the window of corrosion criticality. **Figure 6**Figure 6 shows how ILI data driven projections played out in each view.

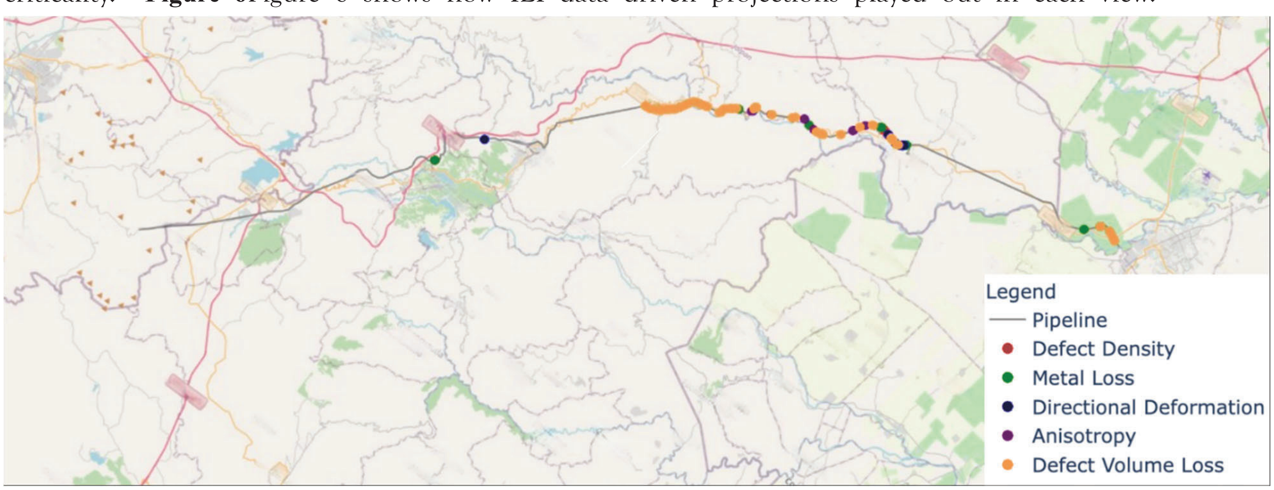

Figure 6. Multiview Convergence

Example Application – Material Verification Optimization

As discussed by Sun, et. al., at IPC 2024[5], we see that machine learning can be applied to datasets to predict pipeline operating stress levels (% SMYS) in cases of incomplete primary data, such as grade and wall thickness. In the paper, the authors present a case for prioritizing manual record reviews to optimize risk mitigation efforts. The study they presented employs regression and classification models, using specific algorithms, to guide integrity assessments efficiently. The iterative methodology confirms the value of integrating machine learning into the overall compliance picture.

Using the **MAOP Reconfirmation System of Record** as a nexus for the decision-making process, we see that building out robust datasets from the onset can be beneficial as we proceed on the road to 100% verification under 49 CFR § 192.624 / § 192.632.

Other Applications and Integrity Concerns

Pipeline integrity management involves addressing multiple challenges beyond corrosion and material verification. Following are some key integrity concerns currently being addressed through digital twins and AI.

- **Weld and Seam Integrity**: Ensuring the long-term performance of welds and seams is critical for pipeline safety – as well as adherence to the Mega Rule through ECA activities. Advanced analytics and inline inspection (ILI) technologies, such as phased array ultrasonic testing, are increasingly being used to identify issues like lack of fusion, low-toughness welds, and selective seam weld corrosion.
- **Cracking**: Cracking mechanisms, including stress corrosion cracking (SCC) and seam weld cracking, continue to pose significant threats to pipeline integrity. Integrating predictive analytics and machine learning with ILI data allows operators to detect, model, and prioritize repairs for crack clusters.
- **Predictive Modeling**: Predictive models based on "like and kind" data have emerged as a valuable tool for assessing integrity in pipelines with limited historical data – as with the material verification example above. By leveraging insights from pipelines with similar material properties, operating conditions, and degradation mechanisms, operators can

[5] Sun, Xiaoyu, et. al. 2024. *Advancing Data Completeness and Strategically Directing Record Reviews with a Machine Learning Approach*. International Pipeline Conference (IPC) Conference Calgary, September 23-27, 2024.

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make informed decisions about maintenance and risk mitigation strategies, even in data-sparse environments.

As a nexus for decision making processes as well as the fundamental asset and and integrity behind the decisions, Penspen's THEIA platform provides a robust framework for developing digital twins through the MAOP Reconfirmation System of Record. By consolidating and aligning data from multiple inspections, consolidating with other datasets and leveraging predictive models, THEIA enables operators to create a comprehensive, perpetually updated record that supports both immediate decision-making and long-term planning.

Conclusion

Pipeline integrity management is undergoing a fundamental transformation as operators adopt advanced technologies like digital twins and AI-driven platforms into their existing workflows. These innovations, exemplified by tools such as CausX AI and Penspen's THEIA, empower operators to move beyond compliance and tackle complex challenges like corrosion, cracking, and geohazard threat assessment with greater precision and efficiency.

By integrating large datasets from multiple sources into dynamic digital twin models, operators can proactively manage threats, optimize resource allocation, and prioritize maintenance activities. These proactive approaches not only reduce operational risks but also align with the evolving requirements of the Gas Mega Rule, providing a strategic advantage in achieving compliance while minimizing costs.

As the industry moves forward, the application of robust digital twins and AI will play a central role in addressing future challenges, such as transitioning pipelines to hydrogen service and integrating renewable energy infrastructure into operator portfolios. Operators who embrace these tools will be well-positioned to enhance safety, ensure regulatory alignment, and build a foundation for long-term operational resilience.

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Appendix

CausX AI is a new genre of artificial intelligence proprietary to Senslytics, that is rooted in epistemology and causality and built to overcome the challenges ML faces. It is designed to model rare phenomena, sudden extremities and situation-dependent time-delayed events. It also finds applications in various industry use cases where decisions rely on interpretation and estimation. Particularly in these cases, it is most important to be as definitive as possible because significant cost and impact can hinge on these decisions. Corrosion in the pipeline fits this bill perfectly.

CausX AI – Ballparking Scientifically

For centuries, mankind developed the pool of scientific knowledge by developing theories or by conducting experiments, but the rise of computational power shifted our reliance towards data-driven correlations, often sacrificing causality and explainability. At the same time, simulation moved towards physics-based modeling by reinforcing constraints and knowledge from fundamentals of physics, but unfortunately this approach is also faced with considerable challenges from simplified assumptions, difficulties in implementation and its incapability of modeling spontaneously adaptable systems like living organisms that display sudden extremities.

Modeling and Understanding Situations: In the realm of machine-learning correlation-based models, outliers are ignored, and singular activation functions are fine-tuned to fit the data by reducing variance between an estimation and the corresponding ground truth at every step. In contrast, CausX AI does not base its estimation on a singular activation function. Using situational proximity as the threshold, multiple situational clusters are formed from the ground truth data that are then connected to the neighborhood clusters generating multiple situation-specific initial guardrails. These guardrails follow the constraints, patterns, or trends that are derived from the experts' hypotheses which maps the experts' general expectation of the system behavior a given situation. **Error! Reference source not found.** explains the approach. Unlike one activation function shown on the left in classical ML, CausX AI shows multiple clusters of situations forming multiple guardrails, some mapping the outliers. These initial guardrails are perfected with time as more and more diverse situational data are run through the AI. Situational guardrails are used for estimating system behavior. Depending upon the proximity of the new situation in the background of experience, a ballparking methodology can be applied. Alternately the situational guardrails are translated or extended when the stability of the situational surface supports such operations.

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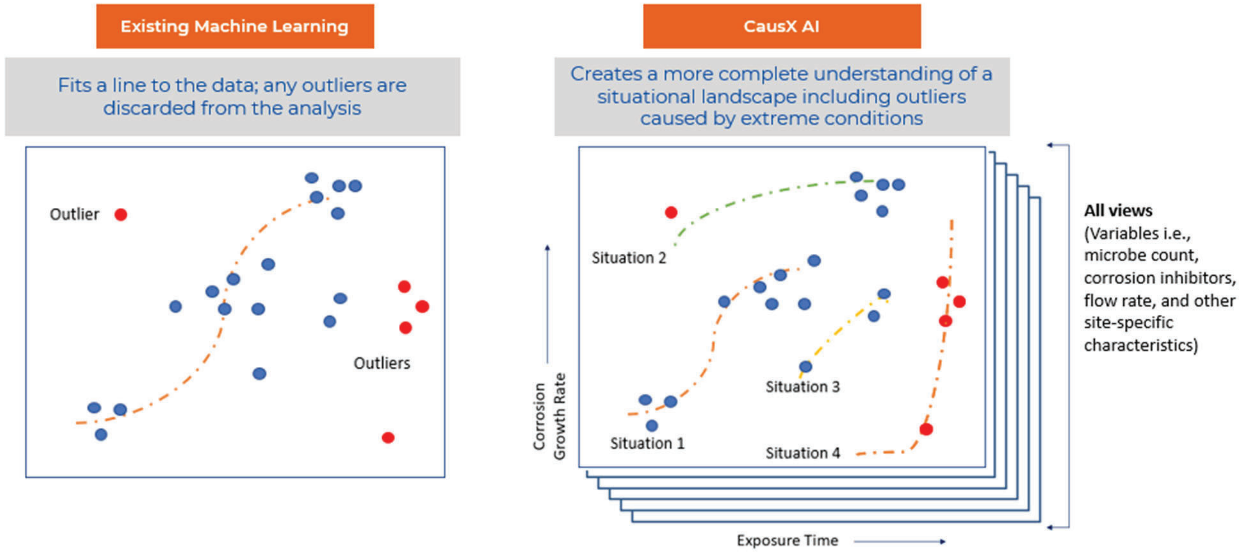

Figure 7: How CausX AI Works

Learning from Ballparking: CausX AI believes in gaining knowledge from all forms of sources as Figure 8 shows. CausX AI learns from experts' hypotheses, empirical formulae, simulation, and equations equally. It particularly attempts to understand the science behind experts' ballparking methods and then refines and extends it to unknown situations. The foundation assumptions of this AI are that in nature, everything happens gradually, and similar situations influence similar systems in similar ways. Therefore, experience from an analogous system can be extended effectively to another system under similar situations for forewarning system behavior.

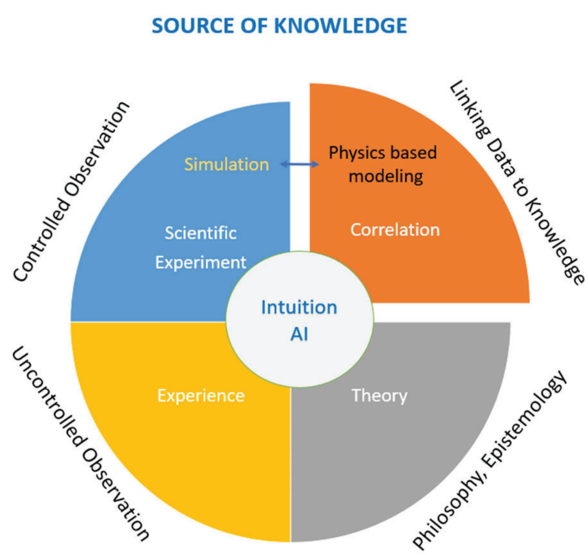

Figure 8: Sources for Intuitional AI Learning

Detecting Rare Events and Time-Delayed Causality: For detecting infrequent events where not enough data is available, CausX AI falls back on experts' hypotheses, which can be seen as processed and rationalized knowledge. Essentially, a valid hypothesis can replace the need for multiple data points, thus making it applicable in areas where data is limited. However, before these hypotheses become reliable and useful, they must undergo bias filtering [1]. Experts' hypotheses help build a scientific fabrication of the AI where the time-delayed causality can be mapped as a causal chain. Influencers that do not have an instantaneous reaction displayed by the system behavior can also be included as part of the model through hypotheses.

Gauging System Vulnerability: CausX AI believes that everything in nature is explainable, and nothing happens haphazardly. The impact of subtle situational changes can remain unmeasurable for a long time and often when blow up, they appear as sudden extremities creating emergency situations, however there was nothing sudden about these disasters [2]. Predicting these extremities simply needs an understanding of how the internal integrity of the system has been deteriorating. CausX AI uses a proprietary technique to characterize a system's internal state and its situational context with previous experiences using proximity measures. Figure 9 explains that a system can sustain consistent stress, such as aging while showing nearly no symptoms for a long time but becoming internally vulnerable and then a small external stress variation can cause disruptive failure.

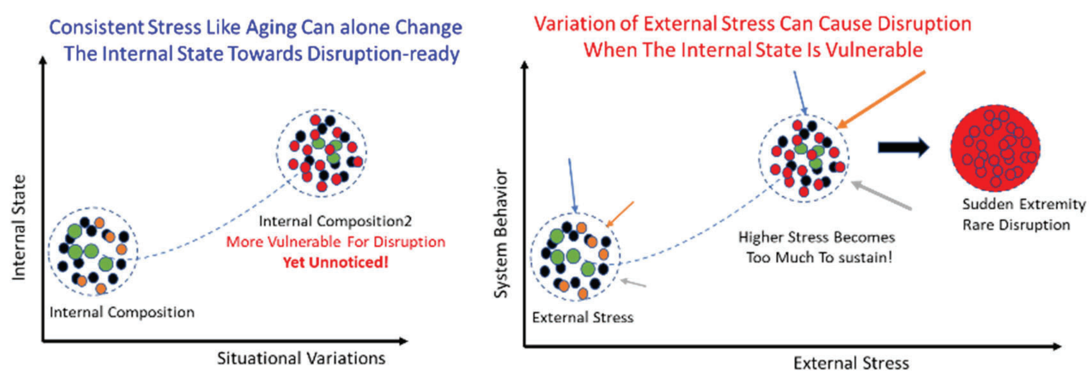

Figure 9: Internal State and Vulnerability

Creating Multiple Views: To be more precise in decision making, one interpretation view is not enough, the system should be examined from multiple views and only when the views converge should an inference be made (Figure 10). For pipeline integrity, the electrochemical view, mechanical view, chemical view, genomic view, fluid dynamic view all can play crucial roles. The more views are added, the more definitive an inference becomes.

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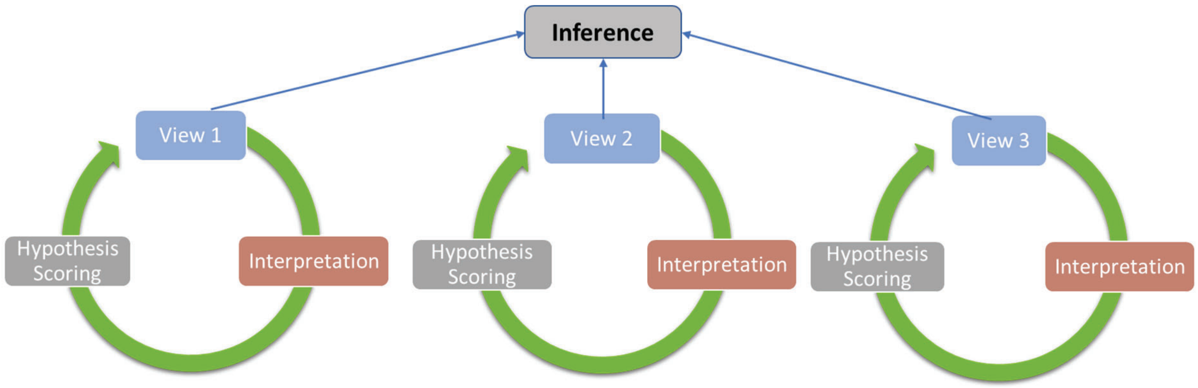

Figure 10: Concept of Multiple Views

Uniqueness of CausX AI

The above discussions clearly show that CausX AI takes a significantly different approach to knowledge modeling [3],[4], [5]. These abilities of CausX AI can assist corrosion modeling and the ability to differentiate between multiple corrosion mechanisms, including MIC.

- Ability to understand heterogeneity in data and detecting truth telling data population by aligning situational expectations
- Ability to conduct recursive zooming and filtering in large pools of data to identify and focus on the outlier's behavior.
- Ability to understand consistency and situational stability by view and dig from experience for a familiarity to mimic behavioral trajectory and estimate outcome
- Ability to correct situational bias, human bias, and generate interpretations from each view
- Ability to converge interpretations towards an inference forming an overall dependability score based on each view's fidelity.
- Ability to generate inference and explanation detailing each step with reference to past experience or hypotheses so surprises with the estimation results are eliminated.
- Ability to detect uninterpretable scenarios: When a situation cannot be effectively modeled using existing knowledge or by extending it, the AI framework identifies the situation as uninterpretable. In such cases, users receive an alert message indicating that a reliable model could not be established under the current circumstances, though an attempt is made to provide the best scientific guesstimates, where possible. In all these cases, experts are prompted to add new hypotheses, modify existing hypotheses or to add new views or variables.
- Ability to adapt and add new knowledge: The framework remains open to incorporating newer knowledge. It achieves this by either adding fresh hypotheses, modifying existing ones or adding new Views or variables which is discussed in the next section. This flexibility ensures the

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openness of the model that can evolve and accommodate emerging insight towards modeling unknowns.

Benefits

CausX AI is being designed to identify all forms of corrosion, both internal and external. Once the corrosion mechanism is identified the future growth rate can be more accurately predicted. In addition, mitigative actions can be taken in a much more targeted manner. Because the AI is based on causation, it is more explainable. It will eventually provide the drivers of corrosion in order of influence along with the expected consequences (Figure 9) so that integrity engineers can assess whether they agree with the AI's logic.

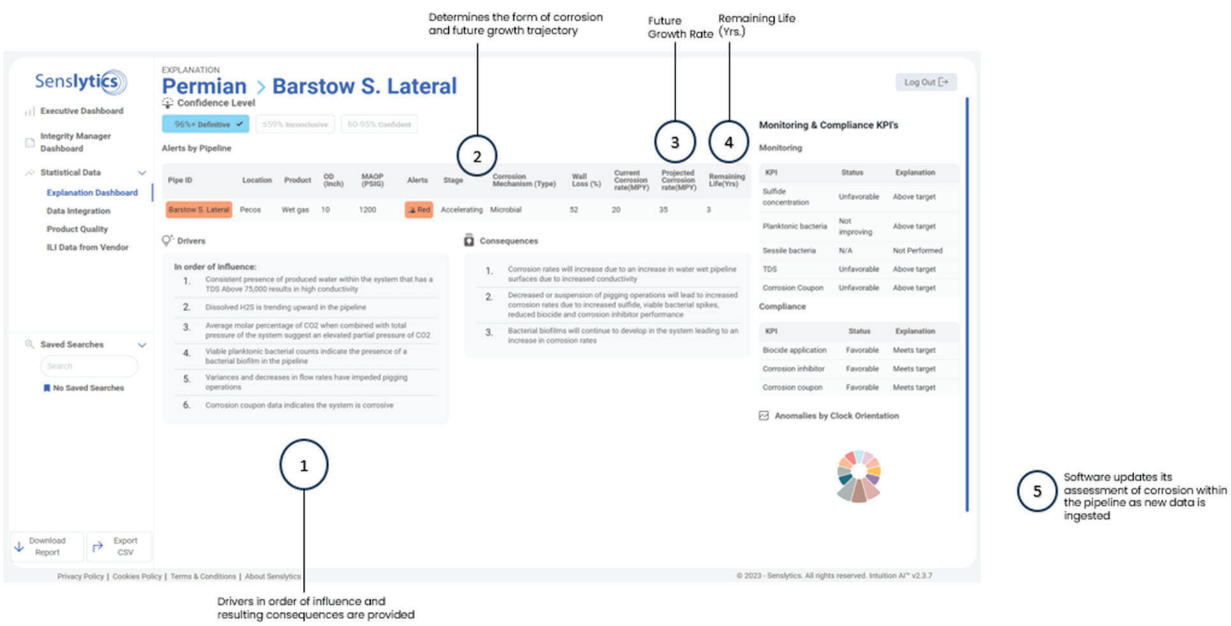

Figure 9. Drivers of Corrosion

Additionally, combining the causal and multi-view nature of CausX AI means that it will not provide an answer when it does not have reason for confidence. No longer will engineers have to rely on probabilistic estimates. Instead, they will receive feedback on which locations have a corrosion problem, which do not, and which need their detailed attention or further analysis because the AI is unsure. This will free integrity engineers to focus on a more reliable list of problem areas rather than receiving false positives and false negatives. Furthermore, they can devote manpower and dollars to not only the problem areas, but to the areas that require a uniquely human problem-solving and reasoning capability – the uncertain areas of the pipeline.

Based on a clearer understanding of a pipeline's corrosion status and the cause, operators can optimize ILI assessments, moving the next tool run earlier or later based on a better understanding of corrosion.

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CausX AI's application to corrosion can lead to:

- reduced failures and incident-related costs
- reduced digging costs
- optimized chemical usage
- increased engineer availability
- longer pipeline asset life

The greatest benefit may still be knowledge retention. So much of the pipeline workforce is at or nearing retirement age. When those veterans walk out the door, so much knowledge leaves with them. By converting that expert knowledge into code, it allows a young engineer to have the SME assistance that would otherwise be gone.

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Appendix References

[1] Chakraborty R., et. al. 2018. *Data Insight and Intuition System for Tank Storage.* US Patent Number: 10,061,833 B2, Senslytics Corporation.

[2] Chakraborty R., et. al. *Method of Intuition Generation*. US Patent Number: 10,073,724 B2, Sep 11, 2018, Senslytics Corporation.

[3] Chakraborty R., et. al. *Method of Intuition Generation*. US Patent 10,445,162 B2, Oct 15, 2019. Senslytics Corporation.

[4] Chakraborty R., et. al. *Methods and Systems Correlating Hypotheses Outcomes using Relevance Scoring for Intuition based Forewarning*. US Patent 11,226,856 B2, Jan 22, 2022, Senslytics Corporation.

[5] Chakraborty R. 2023. *Intuition AI – A Hypotheses Iteration based Scientific Learning Framework*. American Causal Inference Conference (ACIC), Austin, Texas, May 24-26, 2023.

[6] Chakraborty R. 2024. *Applying Intuition AI To Assist Understanding of Complexity in Microbial Influenced Corrosion*. Association for Materials Protection and Performance (AMPP) Annual Conference, New Orleans, March 3-7, 2024.

https://doi.org/10.52202/078572-0072