HOW AI CAN RESHAPE THE DATA ANALYSIS PROCESS OF ILI TOOLS

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1. Abstract

Trapil, the French leader in the transport of energy products by pipeline, has been developing and operating inspection tools for over 40 years to detect corrosion, metal loss, geometric defects, cracks and laminations that can affect pipelines.

With the advent of phased array technology and the increasing frequency of inspections due to the demand for ever more abundant, reliable and accurate data, the amount of data recorded by ILI tools for analysis has recently increased dramatically. Managing this massive flow of data is a major challenge for ILI operators, who are committed to maintaining the highest quality of service for their customers while minimizing report delivery times. To meet these new challenges, TRAPIL has launched an ambitious research programme based on advanced AI technologies. Initially dedicated to the search for geometric faults and missing metal, this presentation will focus in particular on crack detection and identification, the results obtained and their effect on the ILI data analysis process.

2. Introduction: Context and Challenges

Since July 2020, French regulations regarding transport pipelines have introduced new requirements for in-line inspections. These regulations mandate an increase in both the types of inspections and the frequency of control operations.

At Trapil, we have proactively adapted to this growing demand for in-line inspections. Our strategy has focused on two key objectives: developing a range of combo tools capable of performing all types of inspections across multiple diameters, and enhancing our data analysis capabilities.

3. Innovative Solutions: ILI Tool Development and AI Integration for Enhanced Analysis

3.1. Introduction

Trapil has been developing and operating UT inspection tools under the XTRASONIC name for over twenty years. They are used to detect, identify, size and locate the most common defects present in pipelines, such as corrosion, dents and laminations. This technology is based on the use of single-element sensors and the pulse-echo control principle.

More recently, a new tool generation has been carried out and a fleet of inspection tools is now available to carry out axial and circumferential crack detection. This technology is based on the use of phased array sensors, and these tools are called XTRASONIC-NEO.

All these tools generate a very large volume of data, which is used by qualified analysts.
Faced with this large volume of data and thanks to the knowledge and experience of data analysis acquired over all these years, TRAPIL has committed itself to the production of a technology based on artificial intelligence (AI). The aim is to offer analysis assistance that automatically detects, identifies and locates the main faults encountered.

3.2. AI as a solution

Artificial intelligence (AI) is becoming more and more widespread within companies, in all sectors of activity. Artificial intelligence (AI) is defined as any tool used by a machine capable of ‘reproducing human-related behaviours, such as reasoning, planning and creativity’.

Companies of all sizes can use AI to simplify complex, repetitive tasks to achieve greater efficiency, improve the effectiveness of processes and cut costs, offer tools for new services, analyses and exploit data from Big Data (mega data), optimize marketing campaigns and targeted advertising, improve customer service: Chabot, virtual assistants, and so on.

3.3. Objective

To use this technology to develop an effective solution tailored to the challenges of in-line pipeline inspection, TRAPIL set itself a number of technical constraints:

- Taking into account the two types of UT data (traditional UT and multi-element UT)
- Compliance with performance objectives, with detection and identification divided into two categories corresponding to the most critical anomalies on the one hand, and all anomalies on the other. The performance criteria are defined in the table below.

The project aimed to validate an AI solution with strong performance based on the following metrics:

- POD (Probability of Detection): Measures the percentage of real defects identified by the model ($\frac{TP}{TP+FP}$), similar to recall.
- POI (Probability of Identification): Evaluates the accuracy of defect classification.
- CF (False Alarm Coefficient): Represents the ratio of false positives to true positives ($\frac{FP}{TP}$), akin to 1-precision ($\frac{FP}{TP+FP}$).

The table below summarizes the validation criteria for the AI tool:

	Validation criteria (compared with traditional analysis)
Probability of Detection (POD)	100% (excluding untreated tubes)
Probability of Identification (POI)	≥ 90%
CF (False Alarm Coefficient)	0.1
Processing time	< 24 hours for 50km

Figure 1: Validation criteria for the AI tool

3.4. AI Solution Development Workflow

The development process began with data acquisition and pre-processing to ensure high-quality inputs. Following a research phase, the model was trained on diverse defects for robust generalization. Rigorous validation ensured compliance with industry standards before deployment.

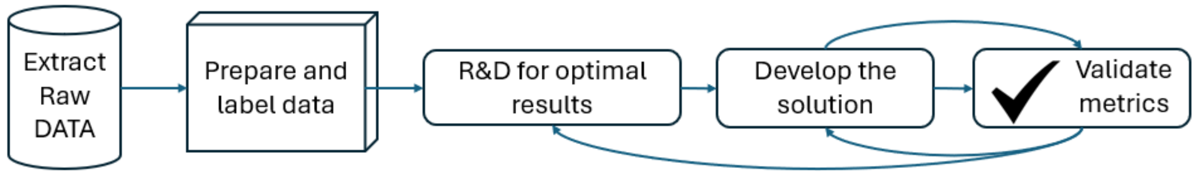

Figure 2: Pipeline for AI Solution Development

3.5. Creating a Usable Dataset

Beyond several terabytes of CSCANs, we rely on a database of approximately 150 indications collected and based on excavation feedback. This file includes details such as defect type (e.g., crack like, crack field) and precise bounding box coordinates. These annotations are crucial for training the model to detect defects accurately.

To build a robust dataset, we had to include:

- Matrices with defects: To teach the model to identify anomalies.
- Matrices without defects: To prevent the model from overfitting and learning to find defects in every image.

Using this technique, we ensure the model generalizes effectively without requiring excessive computation or training time.

3.6. Workflow for Dataset Creation

The data generation workflow follows these steps:

- Traverse the pipe section-by-section with a fixed step size.
- Save matrices with defects, ensuring accurate labelling of defect positions.
- Randomly select defect-free matrices from various sections of the pipe to ensure diverse representation.

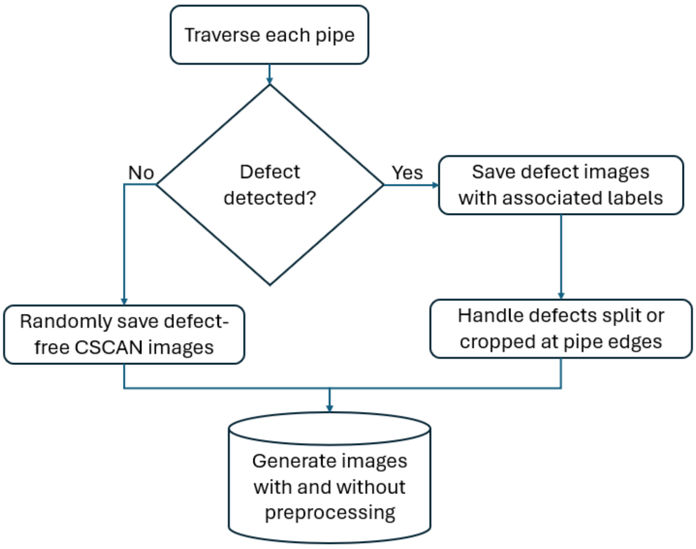

Figure 3 : Data Generation Workflow

To accelerate and secure this critical task, we developed a solution capable of automatically filtering measurement noise and bounding crack-type anomalies. Due to the initial lack of homogeneous data suitable for a deep learning approach, the project focused on creating a "Direct Model" using proven techniques from signal processing, computer vision, and classic statistics. This model was optimized using actual "field" data, representing defects validated on site.

3.7. The Model's Core: Robust Entry Echo Detection

The most fundamental step is the precise detection of the Entry Echo, the US signal reflected by the pipe's inner wall. Theoretically, any signal recorded after this echo is a potential defect.

The Direct Model introduces a more sophisticated approach based on sliding window analysis.

The measurement space (Kilometric Position, Angular Position) is broken down into analysis windows.

Within each window, the median time of all signals is calculated, providing a robust initial estimate of the entry echo that is resilient to outliers (whether noise or actual defects).

This estimate is then locally refined by searching for the maximum amplitude.

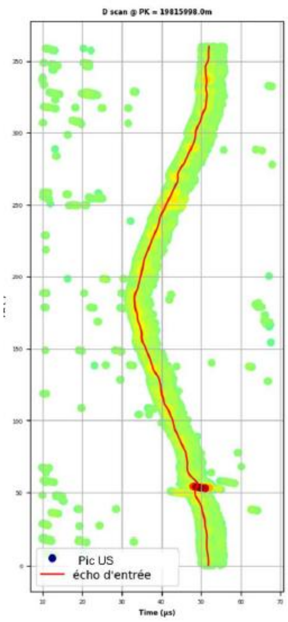

Figure 4 : Robust Entry Echo Detection (Red Curve)

This innovation allows for the generation of a new CSCAN (2D pipeline map) of the post-echo amplitude that is more accurate and naturally filtered of preceding noise, providing a reliable foundation for subsequent analysis.

This section resumes how the automated model cleans the inspection map and finds defects.

The software receives a large scan map of the pipeline, filled with bright signals. Its job is to ignore everything that isn't a real crack, and then draw a box around what remains.

The software begins by cleaning the map to get rid of all false alarms:

- Masking Structures: It identifies and erases large shapes that are not defects, such as welds or other internal structures.
- Managing Weak Echoes: Some faint signals are "phantom echoes"—false reflections. The software adjusts its sensitivity to ignore these specific signals without hiding true cracks.
- Discarding Random Noise: Any signal occurring too late (after the pipe wall echo) is treated as random electronic noise and is simply discarded.

Once the map is clean, the software uses a logical sorting process:

It gathers bright spots that touch or are very close together. Each group is a candidate for being a crack. It immediately rejects any too small candidate—if it's too short or too narrow, it's likely still noise. For the remaining candidates which look real, the software draws a box and expands it slightly neighbouring residual signal to ensure the boundary includes all signals belonging to that single defect.

After defined a list of boxes, we are using a machine learning method where we show the computer thousands of examples of annotated real cracks and noises artefacts

What the Computer Learns From (The Data):

For every potential flaw, we give the computer simple data points, like a spreadsheet of selected relevant features:

- The flaw's size.
- Its total energy (how strong the signal is).
- Whether it appeared on the second inspection run.

The Chosen Tool: We used a fast and efficient learning tool based on Gradient Boosting Decision Trees [1]. It's great for handling this kind of simple, organized data.

Next Steps (How to make it Better): We can make the system even smarter by:

- Giving it more clever physical characteristics to look for.
- Trying different learning tools or combining them.
- Adding more verified crack examples to its training data.

In the end, the software presents analysts with only these precise boxes, allowing them to focus immediately on the actual threats.

Conclusion and Future Scalability

The Direct Model is a robust and highly configurable solution that addresses TRAPIL's need for automated crack analysis. Its modular functional block structure makes the model naturally scalable and adaptable: should a new type of noise emerge (new pig generation, data updates), a new block can be seamlessly integrated without overhauling the entire system.

This model marks a crucial step in the transition towards faster, more reliable, and less initial human-intensive non-destructive testing (NDT) inspection.

Furthermore, the model results can help improve the human analysis workflow and also help systematize quality data collection which in return can be fed to the model to make it more robust.

3.8. Evaluation and validation in comparison with traditional analysis

To validate the detection performance of the solution, we subjected the process to a selection of 129 real crack signals observed in the field. The table below shows the results obtained in terms of POD and CF (false alarm rate).

Probability Of Detection (POD)	**95%**
CF (False Alarm rate)	**2.2**

A second test on signals analysed without available field feedback was carried out, the table below shows the results obtained.

	pipeline # 1 20'' x 45 km	**Pipeline # 2 20'' x 80 km**	**Pipeline # 3 12'' x 110 km**
# cracks reported	31	487	15
POD	91%	93%	100%
CF	3	8	2.2

4. Quantifiable Benefits of AI-Enhanced Data Analysis

Quantifying the benefits of AI integration into our data analysis workflow is essential to understanding its impact. By comparing the traditional workflow with the AI-optimized process, we can clearly demonstrate the efficiency improvements and time savings achieved. The following section outlines the specific areas where AI has delivered measurable results, focusing on the reduction of traditional analysis time and its contribution to meeting regulatory deadlines while maintaining data accuracy and reliability.

4.1. Traditional data analysis workflow

The traditional data analysis workflow for in-line inspection (ILI) tools at Trapil is structured in a series of critical steps to ensure accuracy, efficiency, and compliance with regulatory requirements.

The process begins with the ILI tool run, where the inspection device traverses the pipeline to collect raw data. This is followed by the retrieval and classification of data, ensuring that all inspection data is properly organized and stored.

Once the data is collected, it undergoes a step of validation communicated to the client according to the POF 2021 criteria, where calculated indicators are shared to confirm the quality and completeness of the inspection.

The next stage is data processing, which includes automatic weld detection and, where applicable, the reporting of anomalies detected during previous runs. A preliminary report is then generated, summarizing the initial findings of the inspection.

The most time-consuming step in the process is traditional analysis, which involves the detection, identification, and sizing of potential defects. This step accounts for 75% of the total time required for the entire workflow, whereas all other steps require significantly less time (Figure 9). One key reason for this is that the analyst must thoroughly examine the entirety of the pipeline sections covered by the ILI tool, including both healthy and defective areas. As a result, AI-driven automation projects have been primarily focused on optimizing the traditional analysis phase, more particularly the detection stage.

Following this, the results are subjected to a thorough verification process to confirm their reliability and consistency. Once verified, a final report is prepared, presenting the complete analysis results.
To conclude the workflow, a comparative study is performed, comparing the current inspection results with previous data to identify trends and highlight any new or recurring issues.

4.2. AI-Enhanced data analysis workflow

The integration of AI into the data analysis workflow for in-line inspection (ILI) tools at Trapil has significantly optimized the most time-consuming stages of the process, particularly anomaly detection. While the initial stages, such as the ILI tool run and data validation in compliance with POF 2021 standards, remain unchanged, AI-driven improvements are concentrated on the Data Processing and AI Analysis Verification phases.

In the Data Processing stage, AI automates the detection process, which was previously traditional and time-intensive. By taking over this critical but repetitive task, AI ensures that analysts can concentrate their efforts on the portions of the pipeline identified as potentially defective. This targeted approach allows the analyst to focus on refining the identification of defects performed by AI and verifying the sizing calculations produced by the algorithm. This shift not only increases efficiency but also leverages the analyst's expertise where it is most impactful, ensuring a high-quality final analysis.

The most substantial change occurs in the Analysis IA Verification phase, which replaces the traditional analysis. Here, analysts review and validate the AI-generated results, ensuring accuracy in defect identification and precise sizing measurements. This phase now accounts for 50% of the total process time

One of the main challenges in achieving time savings through the new AI-driven analysis workflow lies in the number of false alerts generated by the tool. A high number of false alarms can result in an analysis time that exceeds that of the initial workflow. To address this, we have implemented specific indicators based on the pipeline length and the predicted number of anomalies to evaluate the suitability of using AI for a given pipeline. Additionally, a post-processing step has been introduced to reduce false alarms while ensuring that the initial POD (Probability of Detection) and POI (Probability of Identification) performance metrics of the delivered AI are maintained.

In addition to addressing the exponential workload induced by the new regulations, the integration of AI into the workflow should also enable us to align with the POF 2021 [1] recommendations regarding final report delivery deadlines. These guidelines specify an 8-week timeframe following the ILI inspection to ensure that additional integrity interventions can be carried out within the required periods.

4.3. Quantifiable Benefits of AI-Enhanced Data Analysis

To measure the time savings associated with the AI-driven analysis workflow, we tracked the number of days spent by the analyst team on these analyses and compared them to our internal benchmarks for traditional analysis times.

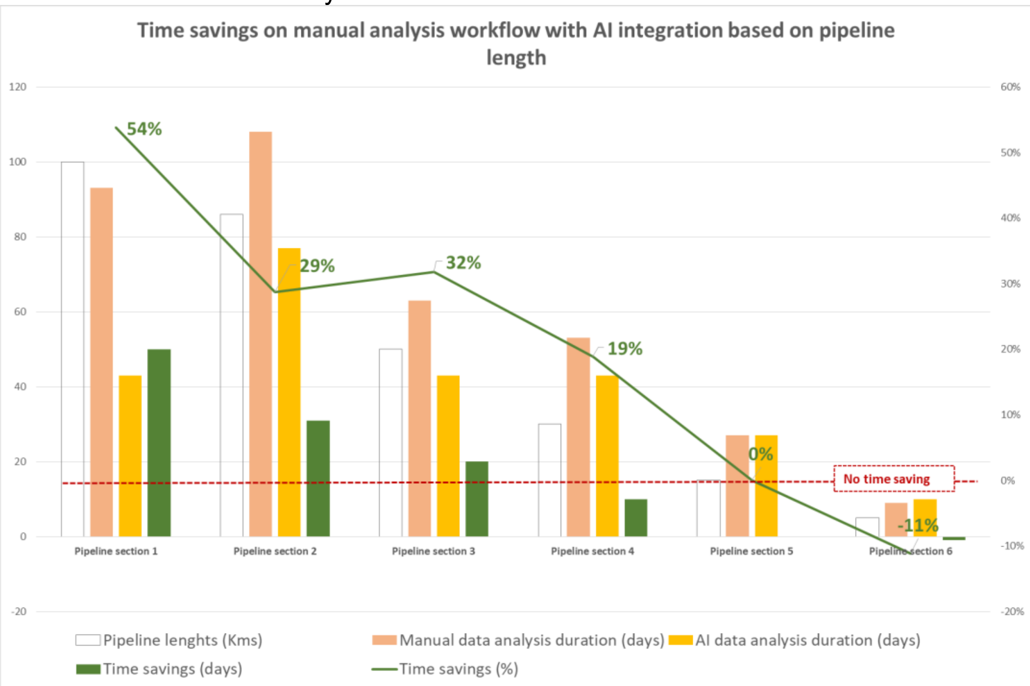

Figure 5 : Time savings on traditional analysis workflow with AI integration

The graph (Figure 5) illustrates the time savings achieved in the traditional analysis workflow when integrating AI, based on pipeline length. The results highlight several key observations:

- **Time Savings Based on Pipeline Length**

The time savings achieved through AI integration in the analysis workflow vary significantly depending on pipeline length. For longer pipeline sections, the benefits are clear: AI automation significantly reduces the time required for analysis, particularly for the detection process, which is traditionally labor-intensive. These long sections, being inherently more time-consuming in traditional workflows, see the greatest impact, with time savings reaching up to 50%.

In contrast, for shorter pipeline sections, the time savings diminish. In some cases, such as Pipeline Section 5, there are no time savings, and for Pipeline Section 6, the AI workflow even incurs a time penalty of -11%. This is primarily due to the higher number of false alarms typically generated by AI on shorter sections. These false alarms require manual verification by analysts, effectively negating the time saved through automation.

However, this observation must be nuanced. AI provides a level of uniformity in detection that is difficult to achieve with a traditional detection workflow. This uniformity contributes to a certain level of reliability, regardless of pipeline length, which can be a significant advantage over traditional processes. While traditional workflows can be influenced by variability in analyst performance, AI ensures a consistent approach to detection, even on shorter pipeline sections.

- **Impact of False Alarms:**

A critical assumption behind these results is that the number of false alarms generated by AI tool tends to be higher on shorter pipeline sections. False alarms require additional analyst verification, negating the potential time savings of AI integration.

- **False Alarms as a Predictor:**

In addition to pipeline length, the rate of false alarms must be considered as an important indicator when predicting the time saved with AI analysis. Short pipeline sections with high false alarm rates may ultimately lead to higher analysis durations compared to traditional workflows.

In conclusion, while AI integration provides significant time savings for long pipeline sections, its efficiency diminishes for shorter sections, particularly when false alarms are prevalent. Future optimization efforts should focus on minimizing false alarms and improving AI accuracy to ensure consistent time savings across all pipeline lengths.

5. Conclusion

The integration of AI into our analysis workflow was primarily driven by the need to reduce analysis time while ensuring a reliable and consistent level of defect detection. This transformation is fully aligned with our corporate strategy, which aims to increase our analysis capacity to absorb the workload generated by the new regulations. By automating defect detection and allowing analysts to focus on cases requiring in-depth validation, we can optimize our resources and accelerate data processing while maintaining a high level of reliability.

The development of this new AI-enhanced workflow represents a major advancement in our analysis methodology. It streamlines repetitive tasks, accelerates processing times, and enables faster decision-making regarding pipeline integrity. Moreover, the efficiency of the workflow depends on several factors, including managing false alarms and optimizing AI models for different defect types.

Among the key improvement areas, the adoption of Machine Learning Operations (MLops) is a strategic lever to fully exploit AI in the analysis process. MLops would allow for the faster deployment of models in production, continuous monitoring of their performance, and automatic adaptation of models to evolving data. By integrating this approach, we could further enhance workflow efficiency and ensure continuous optimization of analysis times.

In the long run, the goal is to sustain this approach, further refine models, and adapt analysis criteria to new industrial and regulatory requirements. This workflow is therefore part of a continuous improvement strategy, ensuring an optimal balance between accuracy, speed, and reliability.

Reference

[1] Gradient Boosted Decision Trees (GBDT), Friedman, J.H. (2001). Greedy function approximation: A gradient boosting machine. Annals of Statistics, 29, 1189-1232.