



ANNUAL SEMINAR

Wednesday 19th November 2025

How AI can revolutionize the data analysis process of crack detection

Stéphane BENICHOU (TRAPIL), Nicolas VAVON (TRAPIL), Allan LEVY (TRAPIL), Théo RYBARCZYK (MP DATA TECHNOLOGIES Engineering Consultancy), Yann DEPLEDT (MP DATA TECHNOLOGIES Engineering Consultancy), FRANCE



Context and Challenges

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

Quantifiable Benefits of Al-Enhanced Data Analysis







Trapil as a pipeline operator ...



TRAPIL's core business is refined petroleum products transportation in the safetiest conditions.

Created in 1950, TRAPIL

- « Société des Transports Pétroliers par Pipelines » operates 3 multi-product pipelines :
- The Le Havre/Paris (LHP), which it owns
- The NATO pipelines in France (ODC)
- The Pipeline Méditerranée/Rhône (PMR)



... and as a service provider



















Inline Inspection Activities in Trapil: A story of over 45 years



MFL ILI tools Metal loss and crack



ALD ILI Tools Leak Detection



XTraSonic UT ILI Tools Dent, metal loss detection



XTraSonic-Neo UT ILI Tools Axial Crack, Dent, metal loss detection



Inertial Measurement Unit Mapping XYZ



T3 UT ILI Tools Illegal taps detection



XTraSonic-Neo UT ILI Tools axial <u>and girth</u>Crack, Dent, metal loss detection

2023



XTraSonic-Neo UT ILI Tools axial / girth Crack, Dent, metal loss detection in 3 diameters

1978

1985

2003

03

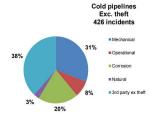
2018

2020

2021

2025

Concawe



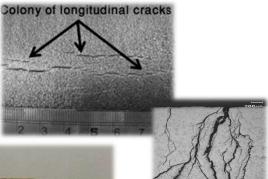
Distribution of major spillage causes for cold pipelines

















Context and Challenges

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

Quantifiable Benefits of Al-Enhanced Data Analysis







The Challenge – Look at Pipeline Anomalies

The Risk: Pipeline Anomalies

- Crack field (depth ≥ 1 mm)
- Crack like (depht ≥ 1 mm)
- SCC (depht ≥ 1 mm)

Code Name: Key Metrics

POD – Probability of Detection

→ Measures how many real defects are correctly detected (like recall).

POI – Probability of Identification

→ Measures how well detected defects are correctly classified (classification accuracy).

CF - Coefficient of False Alarm

→ Ratio of false positives to true positives — evaluates noise level in predictions.

The challenge:

- Strict delivery window of inspection report (<3 months)
- High data volume from UT inspections
- Ensuring the safety of people and property by detection reliability



Our Mission: Build a powerful Artificial Intelligent



- Handle both UT data types effectively
- Meet strict performance standards:

Metrics	Critical anomalies	All anomalies	
POD	100%	95%	
POI	90%		
CF	< 0.1		
Processing time	< 24 h for 50 km		







Context and Challenges

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

Quantifiable Benefits of Al-Enhanced Data Analysis







Al Solution Development Workflow

Understanding the context

Identification of objectives, experts and data





Data understanding and preparation: getting to know the data, identify risks, mitigate if possible

Data collection

Data exploration

Data preparation

Modelling and evaluation: building the solution on prepared data







Creating a Usable Dataset

Full pipeline NDE data

- Contains portions with and without defects
- Data consistency: evaluation of new data should be consistent with training data Every major change in the detection chain can impact performance and require a new model optimization using an updated training dataset.

Ground truth annotations

- Ideally based on excavation feedback
- Includes:
 precise bounding box coordinates
 defect types (e.g., crack like, crack field)



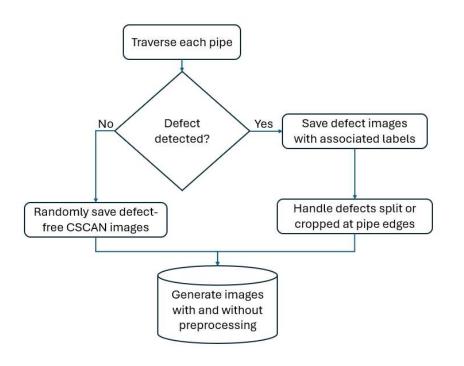
• Homogeneity is important: a labelling protocol should exist and be enforced risk: more complex model training and reduced performance in production







Workflow for Dataset Creation



The task set is one of AI model supervised learning

From the NDE measurement of pipes:

- Compute image-like maps of anomalous ultrasound echoes which enables to pinpoint defects giving their positions on the pipe and their level of criticality
- Identify defects with accurate labelling (position & type), save related pseudo-images (matrices)
- To enable efficient defect type prediction by an AI model, a balanced selection of all possible defect types is necessary
- Also randomly select defect-free matrices from various sections of the pipe to ensure diverse representation.

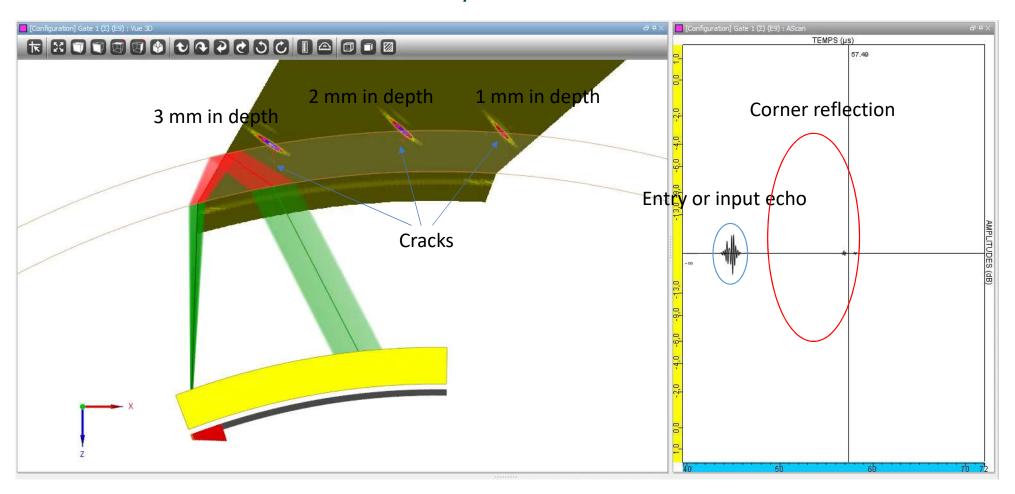
A large quantity of data with a good labeling quality is required to train a deep learning model.

To accelerate and secure data collection: "Direct Model"

- Automatic filtering of measurement noise on generated maps
- First estimator of crack-type anomalies bounding boxes.



A brief introduction on vocabulary

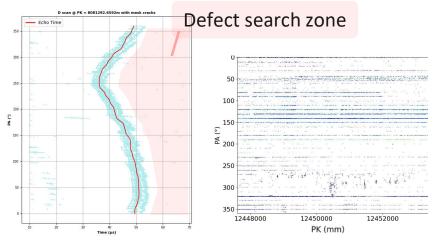


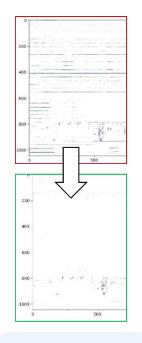




Direct Model

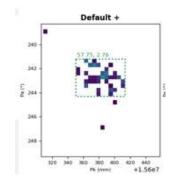
Without enough homogeneous data suitable for a deep learning approach, we used proven techniques from signal processing, computer vision, and classical statistics.





Machine Learning Annotation filter:

- Trained on field-validated ground truth annotations
- Selection of relevant features (size, total energy...) to tag as defect or filter out



Robust Entry Echo Detection CSCAN map computation

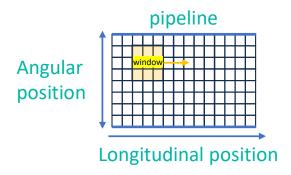
Noise filtering

Rule-based annotation
workflow
+ annotation filtering
ML model



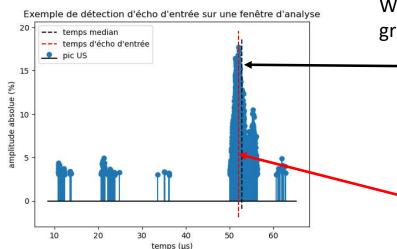


The Model's Core: Robust Entry Echo Detection



At each sampled coordinate, we have the **time-of-flight data of back-propagated ultrasonic pulse**.

At each coordinate, the most prominent back-propagated US peaks are identified. The strongest, called the entry echo, is expected to mark the position of the inner pipeline surface.

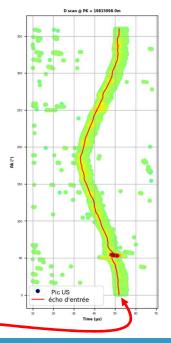


We define a **sliding window** over the full measurement grid:

 For each window position, we compute the median time of flight of all the most prominent US peaks.

This median time is a robust first estimate of the entry echo, little sensitive to noise and outliers.

A most precise estimate is obtained by searching for a local peak amplitude maximum close enough to the first estimate.







Detection performance of the solution using a selection of 129 real crack signals **observed in the field.**

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

High false alarm rate may be explained by the limitation of the direct model and the ML annotation filter due to the limited access to field-validated annotations.





Context and Challenges

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

Quantifiable Benefits of Al-Enhanced Data Analysis



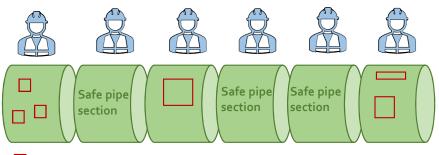




Context and challenges

- Final Report deadline (POF 2021)
- New regulations increase workload
- Traditional ILI analysis is time-consuming (~ 75% of total workflow)

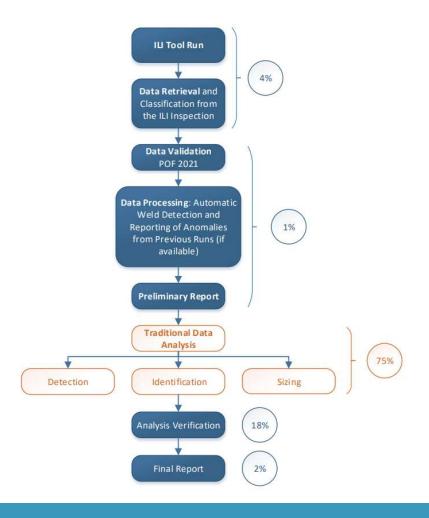
Goal: Reduce data analysis time while maintaining reliability and compliance



Anomalies boxes

65% safe pipe section

35% defective pipe section

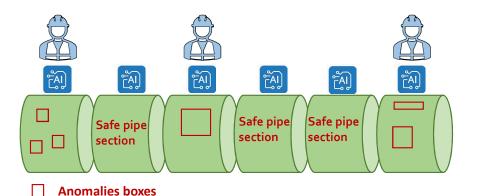


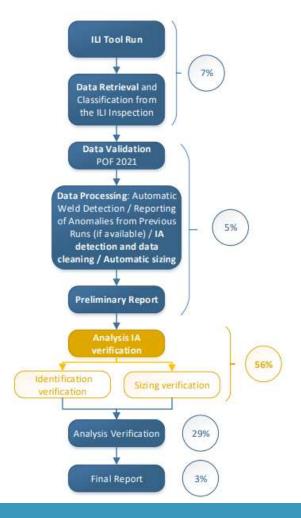




The AI Enhanced workflow

- Detection phase is now Al-driven
- Analysts focus on identification and sizing
- Analysis time reduced from 75% to 56%
- Improves capacity to meet report deadlines while maintaining high levels of accuracy

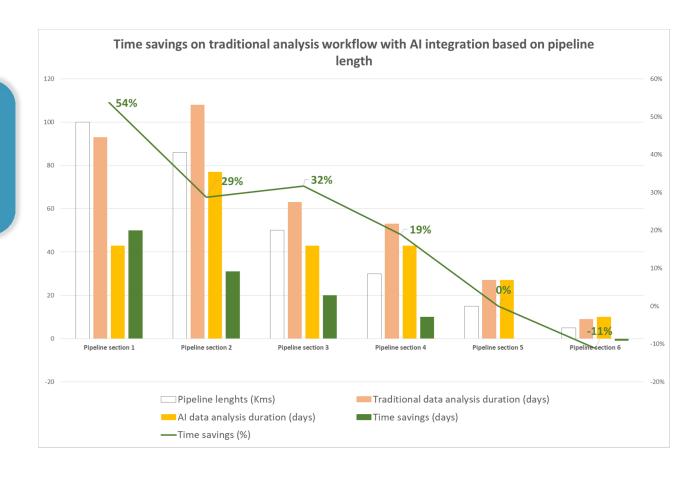






Key results : Time savings

- Time savings up to 54% for long pipelines
- Less gain for short pipelines mostly due to false positives and number of safe pipe section
- Uniform and consistent defect detection



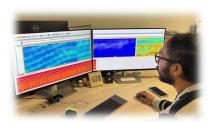


Conclusion: Key Benefits of Al Integration

- Economic benefit: up to 54% time saved
- Enhancing Human expertise: Analysts focus on defective area verification
- Supporting company growth



• MLops integration: for continuous model improvement and fast deployment











trapil.com o1 55 76 80 oo