AI-based and model assisted diagnostic for ultrasonic TFM weld inspection

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Abstract: AI and machine learning for NDT are areas of research that address major challenges of productivity and reliability, particularly for assisted diagnostics (detection and characterization). The development of new solutions based on AI faces problems related to the specificities of NDT, the multiplicity and variability of parameters, combined with a lack of representative databases essential for both training and validation phases. The use of simulation is already recognized as a promising ways to solve the problem of data accessibility, with the advantage of being able to produce large quantities of data and to perfectly control the associated parameters. However, this solution raises other issues such as the representativeness and realism of the simulated data. It is therefore necessary to associate expert skills to extract criteria that are both relevant for a given objective, while ensuring that the simulation, always imperfect, will be particularly representative with respect to these criteria. This paper presents an AI diagnostic study for ultrasonic TFM weld inspection. Based on a V-Weld use case and considering typical defects (toe crack, lack of side wall fusion, slag, root crack, incomplete root penetration), the study compares several strategies of detection and characterization, with different AI approaches (Correlation based, Linear Model, Naïve Bayes, SVM, Neural Network), using and combining simulated and experimental data for the training phase. The results were evaluated on several experiments taking into account uncertainties due to the process, and compared with an expert analysis. The whole study was carried out using the CIVA Data Science software which allows in a unique environment to combine simulation, experiment and AI.

Keywords: weld, diagnostic, Simulation, analysis, UT, machine learning, TFM, SVM, AI

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DE LA RECHERCHE À L'INDUSTRIE

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Context

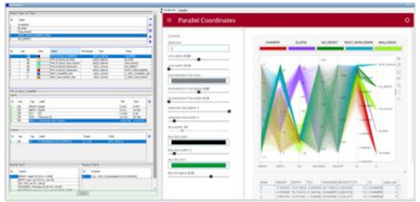
AI requires a large amount of well-mastered data. Major challenge: access to experimental data for AI (quantity and quality)

- Role of simulation: facilitating access to data
  - Fast and unlimited production of data
  - Perfect traceability
- Difficulties
  - Representativeness of the data produced in relation to the experiment

The use of simulation can also be considered in the initial phase for the design, evaluation, and optimization of AI-based solutions

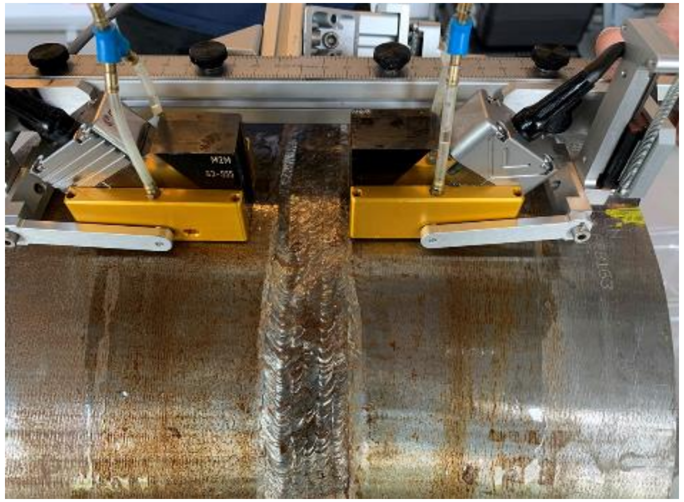
Bringing AI closer to NDE experts
Using of simulation as a facilitator for machine learning
Multi-technique and compatible both with simulated and experimental data

Use of software tools
Simulation / Processing / AI / Analysis



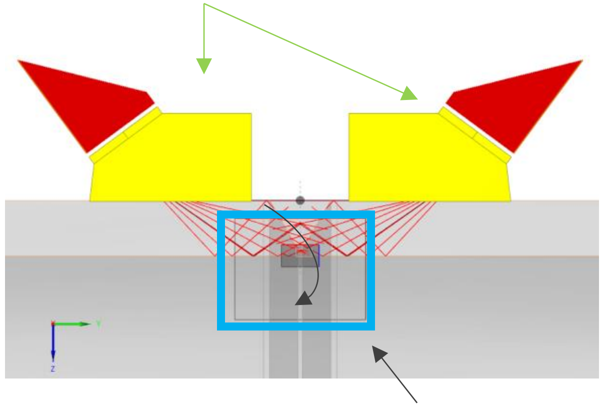
All this study and all images of this presentation are extracted from CIVA UT, CIVA UT Analysis and CIVA DS

Case study



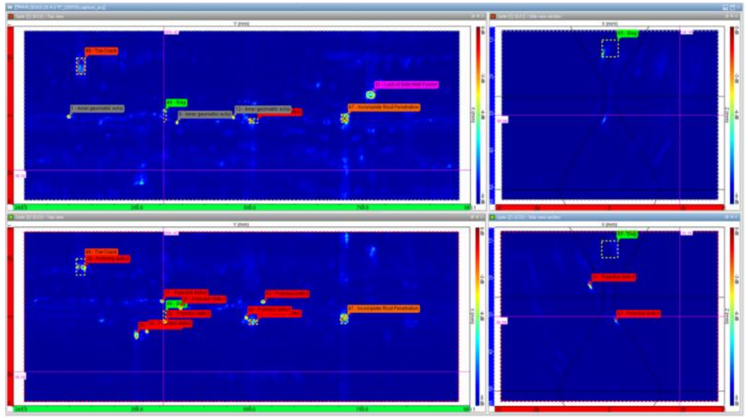
V-Weld 30°
Thickness 25.4mm
Steel tube
Diameter 300mm

2 PA Probes (US and DS) : 5MHz 64 elements : 38 mm x 10 mm
TFM-PWI inspection 43° to 79°, 6 angles



Optimized TFM zone for direct reconstruction (the echoes from the CAP zone will be detected after reflection => visible at the bottom of the zone).

Detection Threshold-12dB

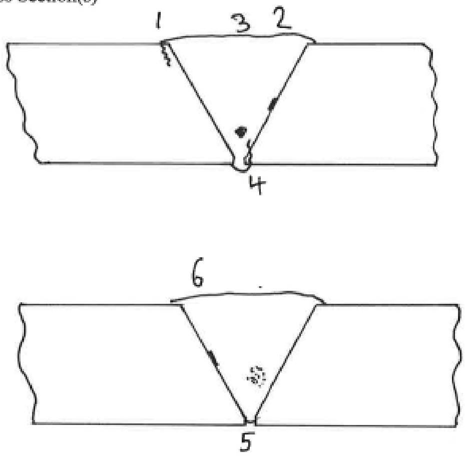


NDE INSPECTION REPORT

ULTRASONIC

Customer	CEA Saclay	Date	28/03/19
Specimen ID	P 28163	Specimen Type	Pipe
Dimensions	25 THK. x 300 DIA. mm	Acceptance Spec.	SI/08/88

Weld/Specimen Cross Section(s)

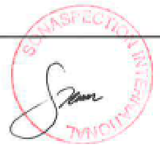


To Scale

Flaw No	Flaw Type	Flaw Length mm	Distance from 0 mm	Max UT Indication dB	Angle
1	Toe Crack	24	113	+ 0	45
2	Lack of Side Wall Fusion	22	248	+ 11	60
3	Slag	16	307	- 6	60
4					0
5	Incomplete Root Penetration	18	709	+ 10	70
6	Lack of Side Wall Fusion	15	766	+ 11	60

Comments:
Misalignment noted.

Inspector	Sam Berriman	Signed



Case Study

Défaut n°	Gate	Type	Amax signal(dB)	ΔY -6dB	Y signal (max)	Y - min -6dB	Y - max -6dB	Z signal (max)	X signal (max)
A	(B1)	Inner geometric echo	-8,9	6	98	96	102	25,49	0,59
1	-	Toe Crack	-7	19	120	116	135	50,03	-17,11
	(B2)	Toe Crack	-7	7	120	116	123	50,03	-17,11
	(B1)	Toe Crack	-10,4	16	124	119	135	49,59	-16,96
1	(B2)	WALL CRACK	-7,7	10	133	127	137	49,15	-17,11
2	(B2)	WALLCRACK	-5,7	7	250	246	253	35,78	6,05
B	(B2)	WALL CRACK	-10,2	5	272	270	275	33,42	5,01
C	(B2)	Potential defect	-9	7	308	303	310	22,26	-5,31
3	-	Slag	-8,3	5	311	309	314	13,73	-1,62
	(B1)	Slag	-8,3	4	311	309	313	13,73	-1,62
	(B2)	Slag	-9,6	4	312	310	314	10,94	1,77
	(B2)	Potential defect	-5,3	7	313	309	316	31,66	1,77
D	(B1)	Inner geometric echo	-10,6	4	339	337	341	24,17	2,65
E	(B2)	Potential defect	-9,4	6	347	344	350	23,14	-3,1
F	(B1)	Inner geometric echo	-10,9	4	465	462	466	24,46	0,74
G	(B2)	Potential defect	-3,6	5	493	491	496	19,17	0,29
4									
	(B1)	ROOT CRACK	-2,5	9	506	499	508	19,46	2,21
	(B2)	ROOT CRACK	-7,3	17	515	501	518	19,32	1,62
H	(B2)	Potential defect	-9,9	8	531	527	535	22,4	-5,16
5	-	Incomplete Root Penetration	-0,6	15	706	703	718	21,08	0,88
	(B2)	Incomplete Root Penetration	-0,6	14	706	703	717	21,08	0,88
	(B1)	Incomplete Root Penetration	-1,1	12	711	706	718	23,58	1,03
6	(B1)	Lack of Side Wall Fusion	-5,7	17	771	760	777	37,83	-7,37

NDT analysis report produced by an expert

6 defects introduced into the specimen and referenced

1. Toe Crack
2. Lack of side wall fusion
3. Slag
4. Root Crack
5. Incomplete Root Penetration
6. Lack of side wall fusion

Other detected indications

A. Inner geometric defect

B. Wall crack (in the prolongation of n°2)

C to H Inner geometric indications

5 available acquisitions (on a same specimen):

- Nominal configuration
- Probe offset (+/- 2mm)
- Distance between probes (+/- 2mm)

Objective of the study: to evaluate the possibilities of obtaining an equivalent inspection report using AI

General methodology for designing an AI diagnostic process

1 Case Study Analysis

- Type of inspection
- Type of data
- Objectives
- Domain of application
- Parameters

2 Training Data

- Experimental
- Simulated
- Type of data
- Experimental design
- Uncertainties
- Coverage

3 Learning

- Extraction
- Dimensionality reduction
- Type of learning

4 Validation

- Performance evaluation
- Sensitivity analysis
- Confidence level

5 Implementation on the field

- Level of automation
- Performance
- Analysis
- Embedded Real-Time

Step 1: Analysis of the case study

1- Business functional analysis

Key points :

Combining information from the **two sensors**

Preserving the **localization** of indications in the image

Amplitudes: significant variability associated with defect size (regardless of defect types)

=> Focus on relative echo amplitudes in the image (normalization for each position)

Detection:

Threshold set at -12dB (without normalization)

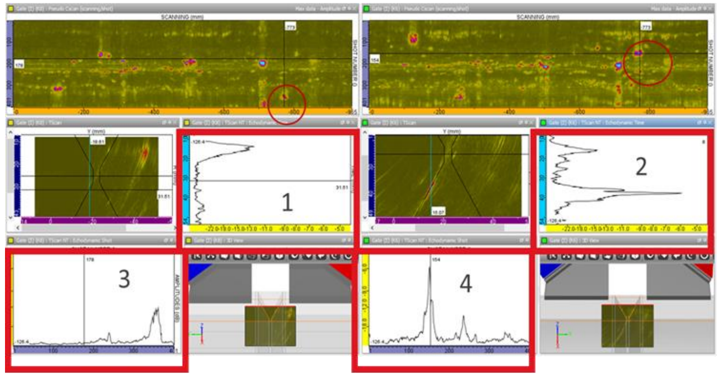
Alternative using machine learning (on normalized data)

Extraction: Four types of extractions will be evaluated

- Position of the maximum value in each image: vector [4]
- Position of the maximum value and amplitude ratio between the maxima: vector [6]
- Horizontal and vertical echodynamics: vector [1428]
- Reduced-resolution TFM images: Image[50,50]

Objectives: Detection and classification of echoes among the following classes:

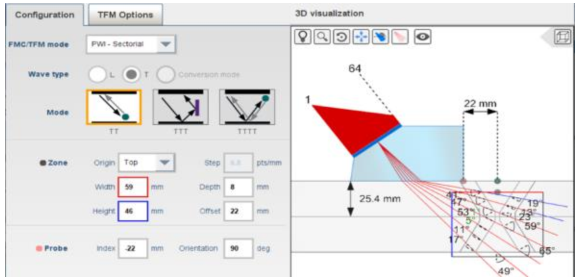
- **Toe** (surface-breaking crack on external surface)
- **Slag** (volumetric defect)
- **Chamfer** (defect along the chamfer)
- **RootFlaw** (weld root defect - crack or lack of penetration)
- **RootGeom** (geometry-related echo due to irregularities on backwall or tube misalignment)



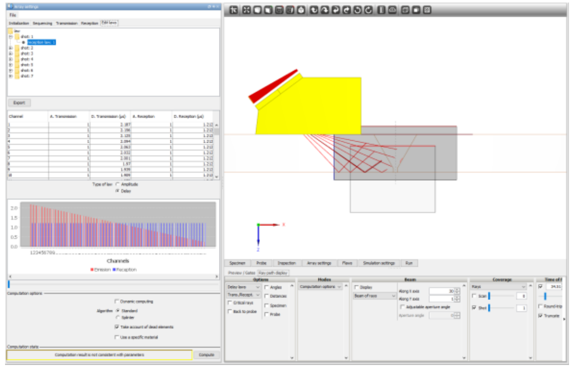
Step 1: Analysis of the case study

2- Configuration and parameters for the simulation

Verification of model inputs
(Facilitated in our case by the compatibility between CAPTURE / CIVA): Probe, focal laws, etc.

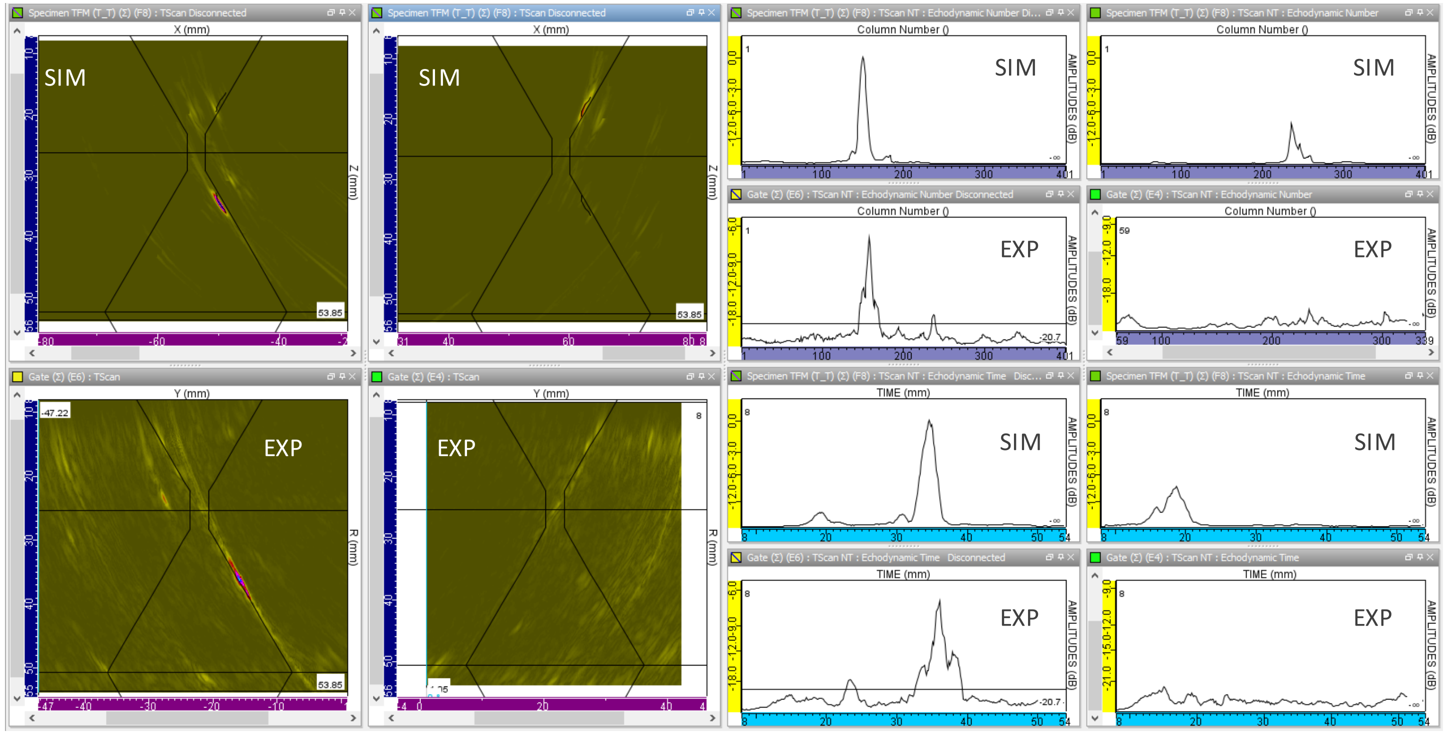


Capture (EDDYFI)



CIVA

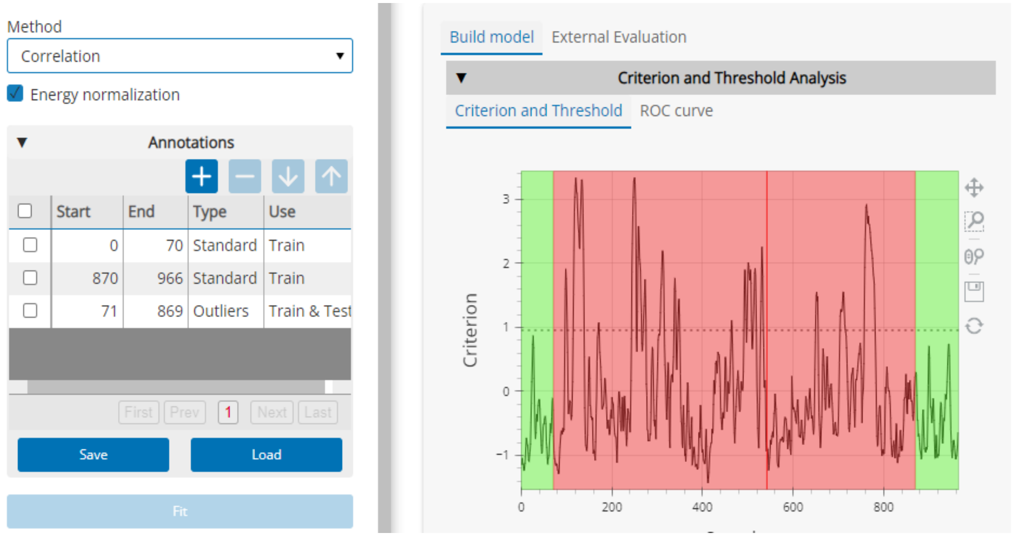
Verification of the validity and representativeness of the model

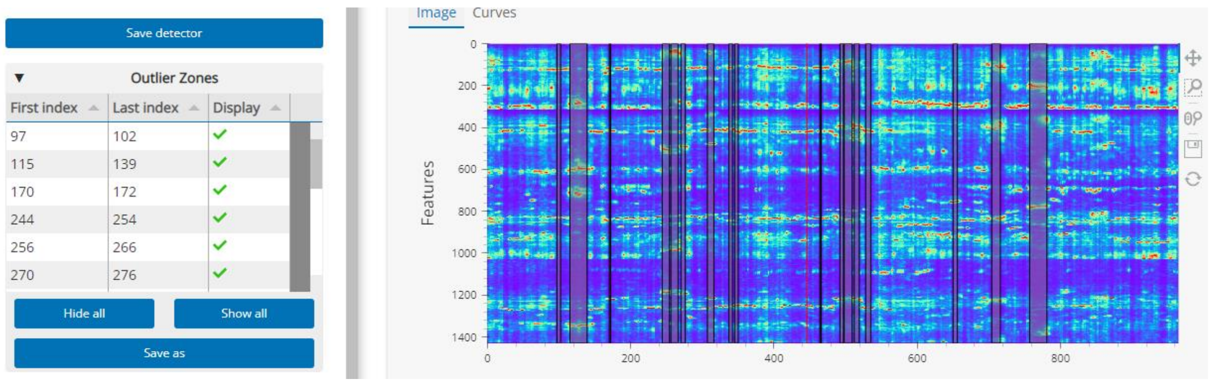


Step 2: Training data — Detection

Learning from experimental data (amplitude normalized by position)

- **Extraction of a defect-free zone**
- **Application of a correlation-based detection algorithm**
  (Extraction of a value by position derived from the correlation between the echodynamics and threshold determination)





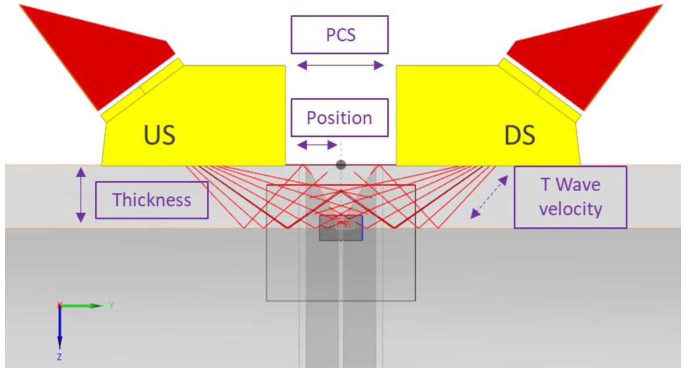
Defect-free zones in green
Threshold determination

Expert-identified zones (based on -12dB criterion)	Zones consistent with the expert's zones		Additional zones detected by the correlation-based detection algorithm	
97->103	96->102			
120->137	115->139		169->173	Indication at -13dB not retained by the expert (geometry echo)
245->251	244->254		256->266	Indication outside the weld zone at -9dB not retained by the expert
268->274	269->276			
308->315	303->316			
336->340	337->342		345->350	Geometry echo at -10dB not retained by the expert
489->495	492->497		463->466	Geometry echo at -11.8dB not retained by the expert
498->517	498->509	512->519		
527->534	528->535		650->656	Indication at -13.4dB not retained by the expert (small surface notch)
703->707	704->715			
758->775	757->782			

Step 2: Training data

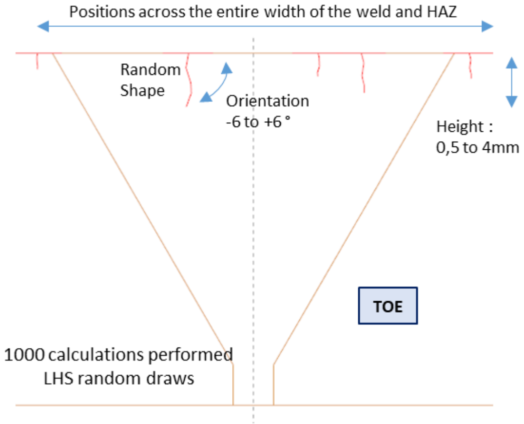
Classification

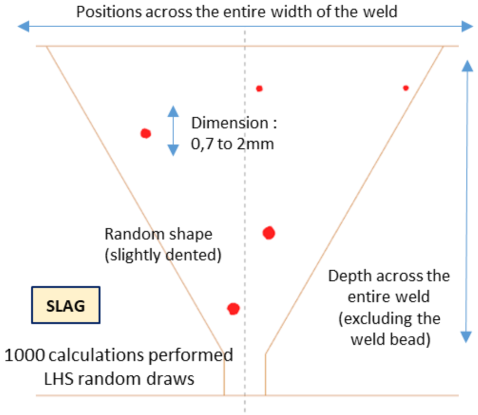
Learning from simulated data
=> Numerical experimental design

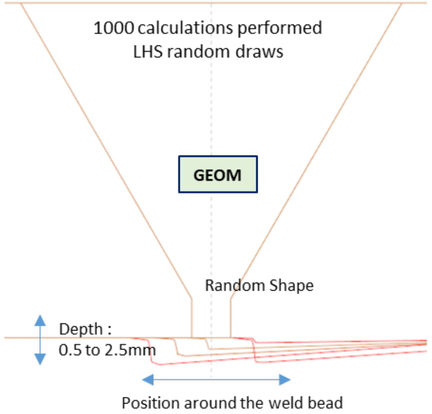


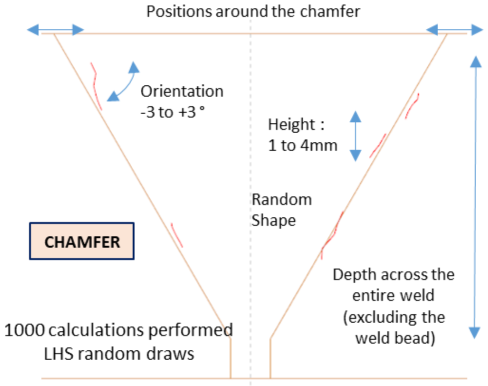
Essential Variables

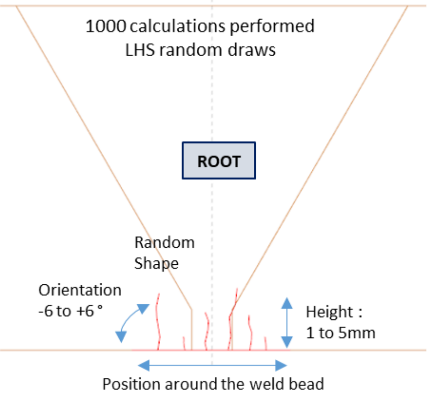
- PCS : +/- 2mm
- Probe misalignment with respect to the weld: +/-2mm
- Thickness : +/- 1mm
- T-wave velocity : +/- 20 m/s

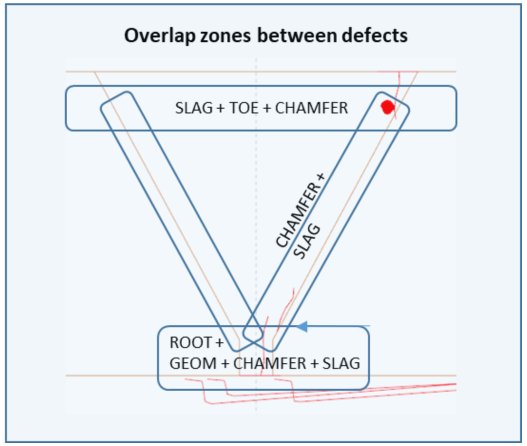




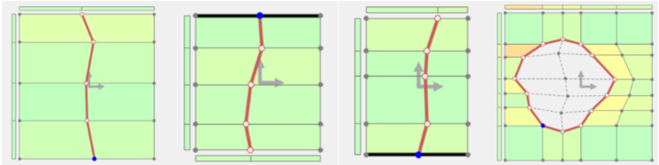








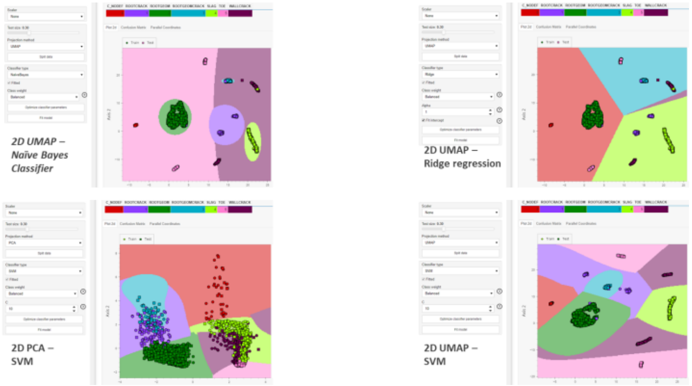
Defects (types, dimensions, positions, orientations, random shape)



1- Linear model classification

- Classifier choice (SVM/RIDGE/NAIVE BAYES)
- Extraction algorithm choice (UMAP/PCA)
- Associated parameters (Number of components, Regularization)

- => first evaluation on simulated data



Tests on simulated data	POSITIONS OF MAXIMUM	POSITIONS AND AMPLITUDE RATIO (US/DS)	ECHODYNAMICS	TFM_PWI 50x50 IMAGES	Average Scores
SVM/UMAP			97,0	92,0	94,5
RIDGE/UMAP			70,0	92,0	81,0
NAIVE BAYES/UMAP			94,0	92,0	93,0
SVM/PCA			99,0	99,0	99,0
RIDGE/PCA			91,0	96,0	93,5
NAIVE BAYES/PCA			97,0	88,0	92,5
SVM	93,0	98,0			95,5
RIDGE	65,0	79,0			72,0
NAIVE BAYES	85,0	95,0			90,0
Average Scores	81,0	90,7	91,3	93,2	

Step 3 : Data-driven Learning

2- Correlation-based classification

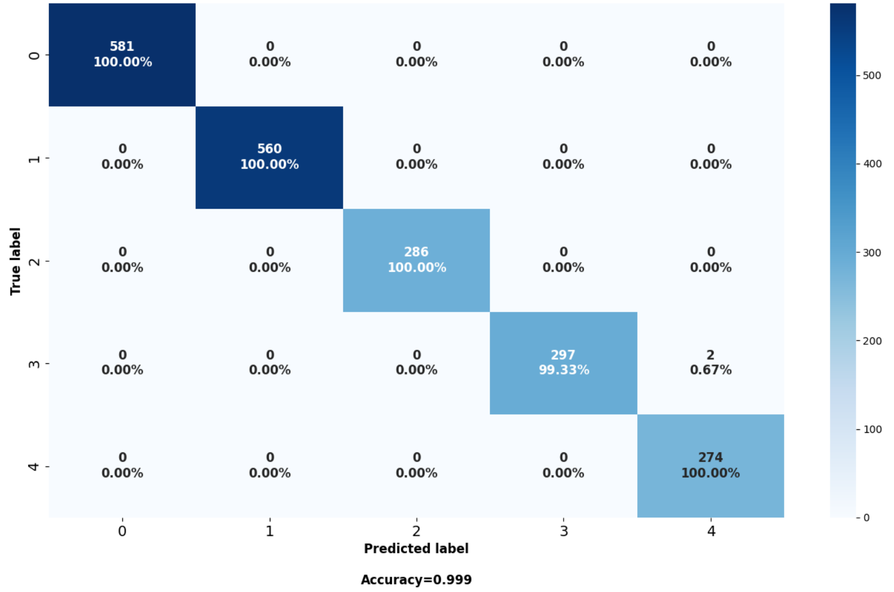
Difficulty in separating geometry echoes from internal wall defect echoes (in the "root" zone)
Exploration of an alternative using correlation (same principle as detection)

Learning geometry echoes based on simulated data
Determination for internal wall defects (replacing multi-defect classification)
If data below the threshold => Classified as "geometry" indication
If data above the threshold => Classified as "defect" indication

3- Neural Network Classification

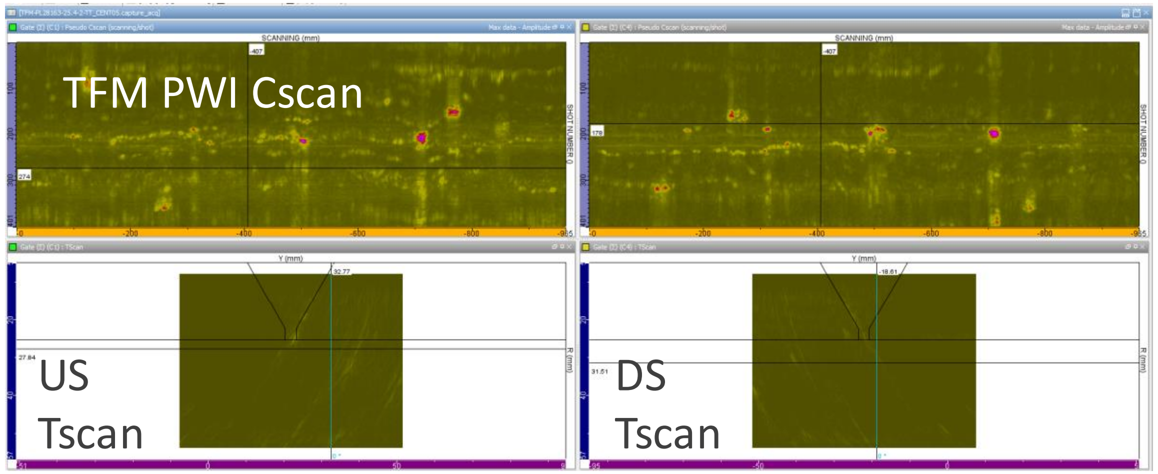
- Architecture selection and optimization
- Number of blocks
- Types of layers per block
- Number of neurons
- Etc...

- Tests on simulated data



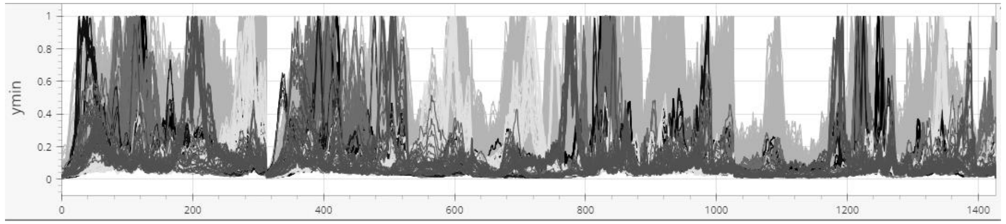
Results obtained by neural network on the validation dataset (obtained through simulation)

Step 4 : *Validation on experimental data*

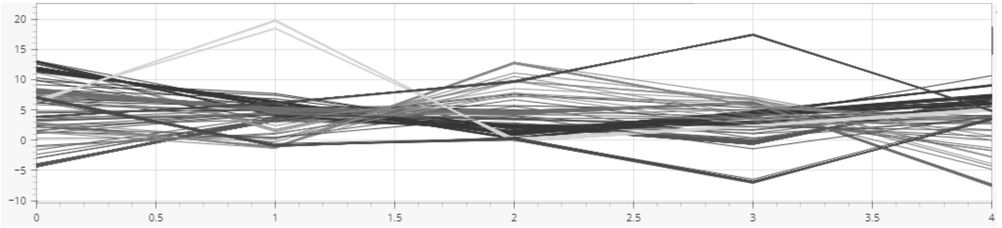


The need to apply a similar extraction as the one used in the learning phase to the experimental data

Exporting the experimental data to CIVA DS
Using CIVA UT Analysis.
Similar extraction (concatenation of echodynamics)



And projection (UMAP 5 in this illustration) using CIVA DS



Principle of the proposed diagnosis and notation

- Evaluation on the -12dB zones.
- For each zone: the predicted class with absolute majority (> 50%) is retained (score measured from predictions for all positions of the indication's zone).
- If no class is predicted with absolute majority, the defect is considered "unclassified".
- In the case of arbitration by correlation, it takes precedence over SVM or NN classification.
- A total of 53 zones were evaluated across the 5 acquisition files. Note that the number of zones and positions to evaluate slightly varies from one file to another due to the identification criterion based on a -12dB threshold.
- 4 types of classifiers were evaluated :
  - SVM
  - SVM + Correlation on ROOT area
  - NN
  - NN + Correlation on ROOT area
- The score is given as a percentage according to the following criteria :
  - Note 1: Percentage of unclassified defects (no majority score among the predictions for the zone of interest).
  - Note 2: Percentage of defects correctly classified (among the classified defects).
  - Note 3: Percentage of defects correctly classified, grouping the ROOT class.

Results

Classifier	Extraction Criterion	Data Reduction	Rate of unclassified cases	Rate of correct classification	Rate of correct classificiation with ROOT cases fusioned
SVM	Positions and ratio of amplitudes US/DS	None	4%	64%	94%
SVM	Echodynamics	UMAP 5	6%	80%	98%
SVM	Echodynamics	PCA 65	4%	64%	94%
SVM	TFM-PWI 50x50	UMAP 10	4%	64%	82%
SVM		PCA 380	6%	67%	84%
SVM + Correlation ROOT	Positions and ratio of amplitudes US/DS	None	6%	84%	94%
SVM + Correlation ROOT	Echodynamics	UMAP 5	6%	86%	98%
NN	Echodynamics	None	6%	86%	100%
NN + Correlation ROOT	Echodynamics	None	6%	90%	100%

General tendency to classify defects very well if the distinction between the two types of echoes in the root zone is ignored.

Some classifiers have a very good ability to predict the defect type for all classes, including the root zone.

The correlation model improves performance for the root zone.

Low scores without expert extraction (here Echodynamics vs Image).

Low rate of "unclassified" defects.

Conclusion

The study can be considered as a proof of concept for AI-based detection and classification, based on simulated data for the learning phase and applied to experimental data.

The entire study (excluding neural networks) was conducted using the CIVA Simulation, CIVA Analysis, and CIVA DS (Data Science) modules.

The implementation of neural networks in CIVA DS is planned for 2024

Next steps and areas of improvement :

- A broader range of experimental data for validation
- A better understanding of the results and failures (representativeness of the simulation, extraction criteria, enrichment of the learning database, etc.).

- Consideration of zones with multiple types of defects (a complexity level not addressed in this study).
- Expansion of cases (thicknesses, types of welds, acquisition schemes, etc.).
- Further exploration of the Neural Network solution (learning from images)
- Transfer learning from simulation to experimental data