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Simulation and AI, two complementary tools for NDE4.0

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Olivier Mesnil

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DE LA RECHERCHE À L'INDUSTRIE

Simulation and AI, two complementary tools for NDE4.0

October, 26th 2022, NDE4.0 Conference, Berlin

P. Calmon, S. Leberre, C. Reboud, R. Miorelli, O. Mesnil

CEA: French Atomic and Alternative Energy Commission- **Public Research Organization**

CEA LIST: The Digital Technology Institute of CEA Tech

Expertise and key programs



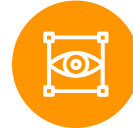
SOFTWARE ENGINEERING



SIMULATION



DATA INTELLIGENCE



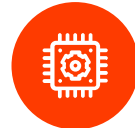
CYBER-SECURITY



ROBOTICS



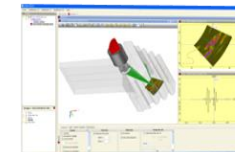
INSTRUMENTATION
& METROLOGY



COMPUTING
& EMBEDDED SYSTEMS

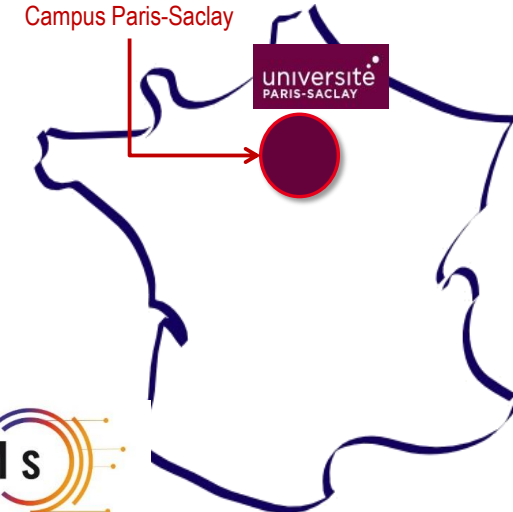


HUMAN-SYSTEM
INTERFACES



At the heart of
Campus Paris-Saclay

université
PARIS-SACLAY



SacHeMs
Saclay High-end Equipment
For the Monitoring of Structure

NDE & SHM RESEARCH ACTIVITY @CEA LIST

- 80 permanent people, 20 PhD students
- Simulation, imaging, AI, instrumentation
- Partenarial research and technological transfer
- Innovation platforms



GERIM2

CIVA
N·D·E·I



OUTLINE

- Key Idea: Simulation and AI are complementary tools for the innovation in NDE technologies
- Illustration on various recent and on progress works at CEA List.
 - Simulation as a data provider for AI
 - Simulation as a facilitator of AI design and implementation
 - AI as a mean to augment simulation capabilities
 - Introduction to new CIVA Data Science module

MAIN APPLICATIONS OF SIMULATION

- Probe design and inspection optimization
- Interpretation of results, diagnostics
- Performance demonstration, POD
- Data provider

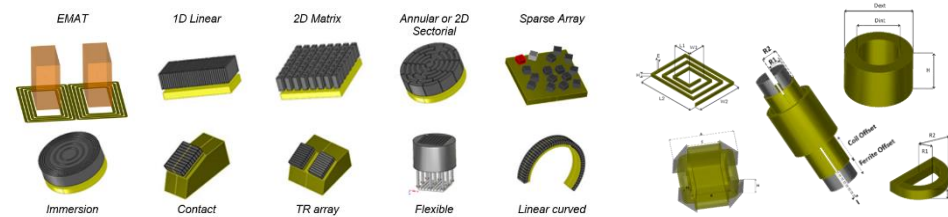
MAIN CHALLENGES

- Multi physics modelling
- Complexity of materials, defects, probes...
- Rapidity and easiness: A tool for NDT engineers
- Confidence and assistance to the operator

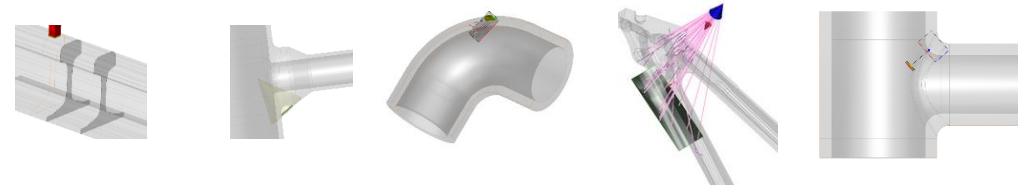
SCIENTIFIC STRATEGIES

- Hybrid modelling: Ray-based, FEM, SIE, etc...
- Data driven models: Metamodels
- Automatization of set-ups (meshing)
- Experimental validation

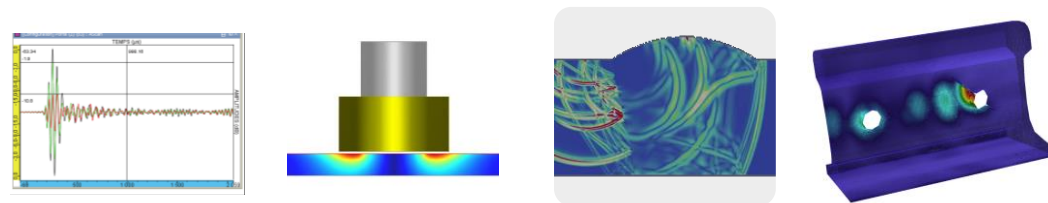
Variety of techniques and probes



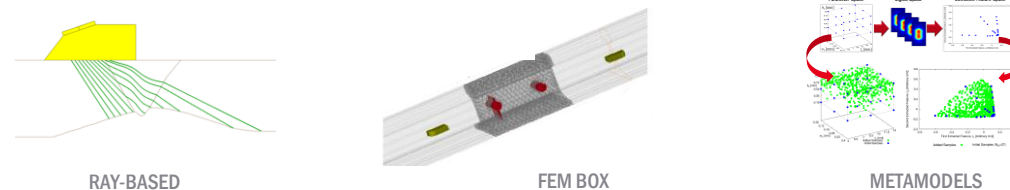
Accounting for complex parts geometries



Displaying Images and signals

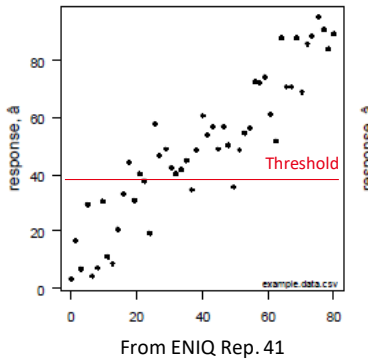


Modelling strategies

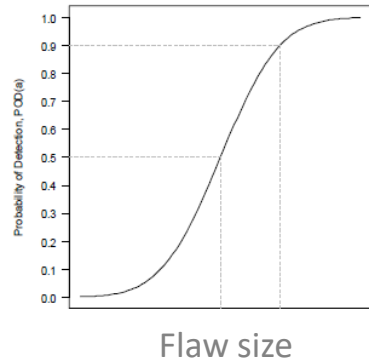


Probability of detection: Accounting for uncertainties and variability

Scattering of NDE results



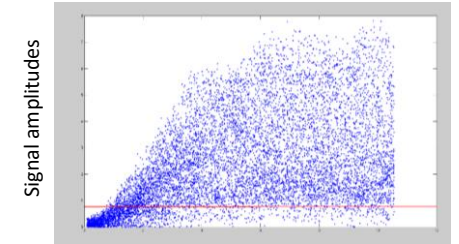
Probability of detection



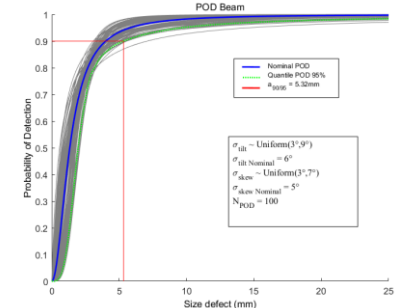
Statistical analysis framework in reference documents: MIL-HDBK-1823A, ENIQ-R41, ...

Example (Manual UT):

Thanks to the metamodel
100 000 computations for one
POD : 1-5 s on a PC



Crack height

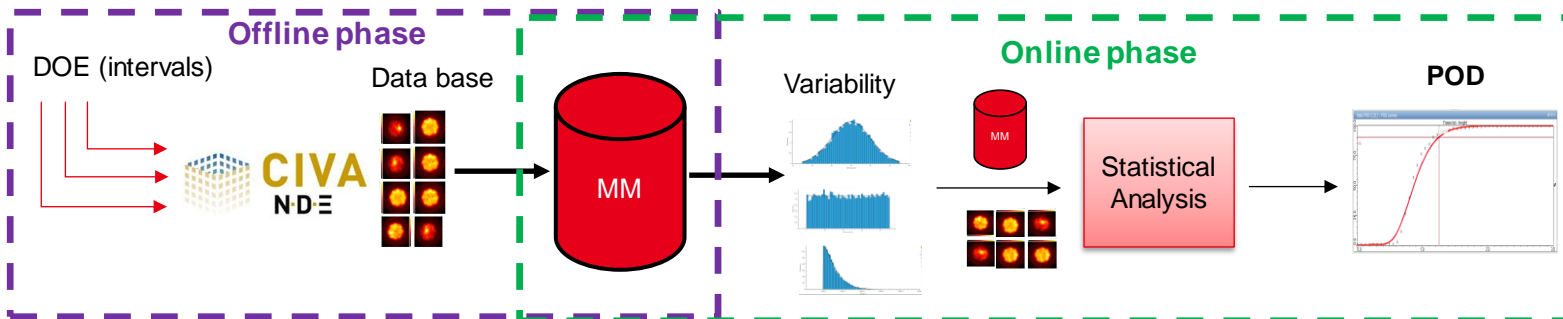


MAPOD: Use of simulation to capture the variability of the influential parameters and provide numerical data for the estimation of POD.



Requires the development of surrogate models (metamodels) :
Machine learning on simulated databases

METAMODELS

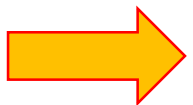


Artificial Intelligence raises high expectations :

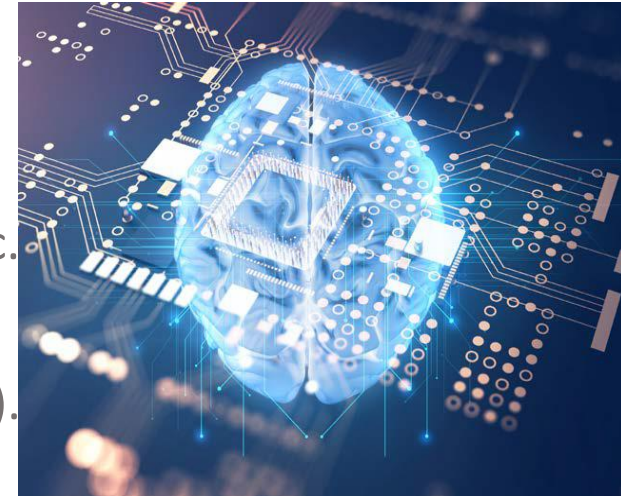
- For the **automation of data analysis operations** (flag of data for review in case of huge volumes of data, possibly application of detection criteria in “easy” cases, etc.)
- **For the assistance to the expert** in a diagnostic or a process of making decision: detection or even defect characterization (identification, localization and/or sizing).

But several challenges in NDE and amongst them:

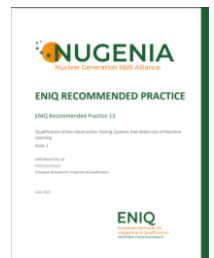
- **Availability of representative databases for training of algorithms** (not so many flaw!)
- Variability of influential parameters and operational conditions
- Robustness, assessment and **qualification methodology**
- Operational implementation (embedded AI)



Simulation as a data provider for training of ML algorithms



April 2021 :
EASA Concept paper



June 2021:
ENIQ RP N°13



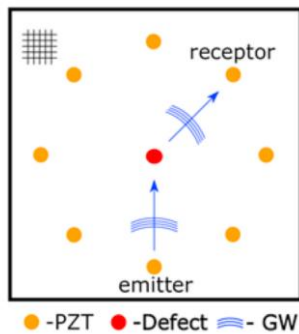
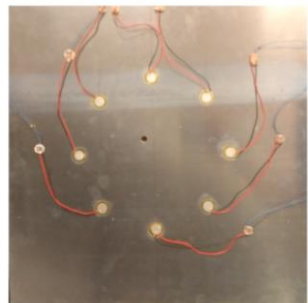
Feb 2022 : ASTM
E3327/E3327M-21

Context: Guided Wave SHM of composite structures

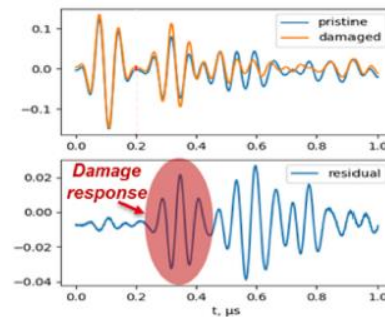
Objective: Develop a Machine learning trained by simulation to locate and size defect from guided waves images.

Guided wave SHM technique

- Set of PZT sensors (~10-40 kHz) surrounding the inspected area
- Model-based imaging (DAS, Excitelet,...) of the residual signals

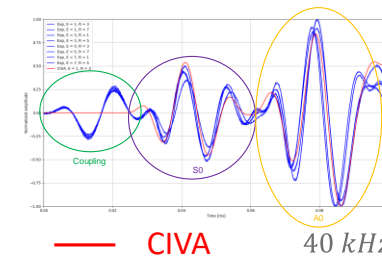


Experimental set-up



Residual signals

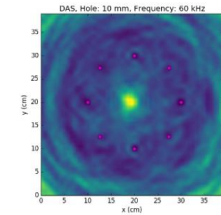
Signals in pristine



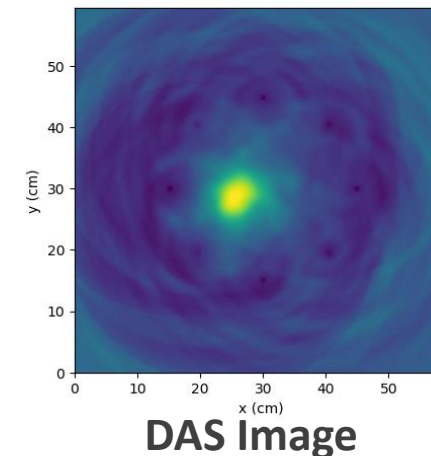
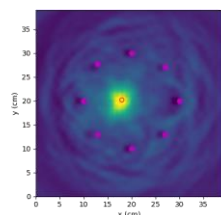
CIVA
NDE I

CIVA-SHM module
3D High order FEM

Experimental

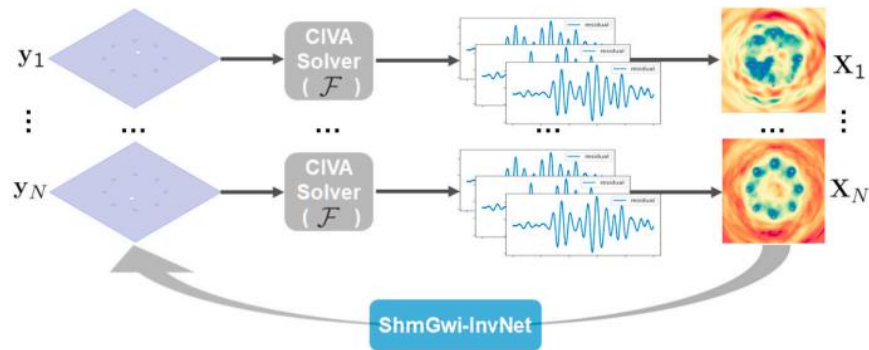


Simulated

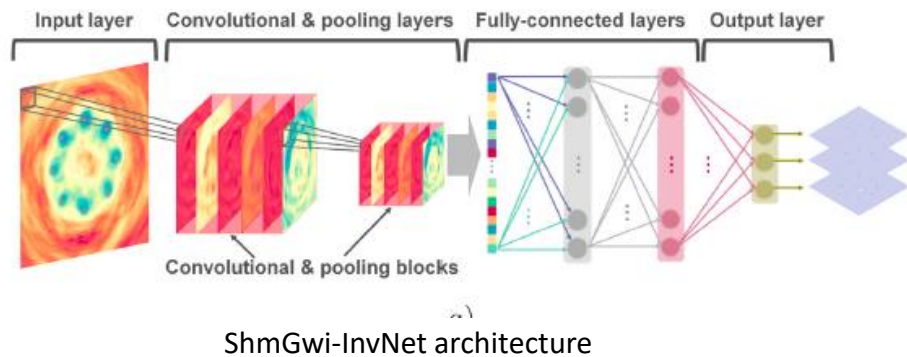


Proof of concept on AI plate containing holes

- Model-driven inversion scheme

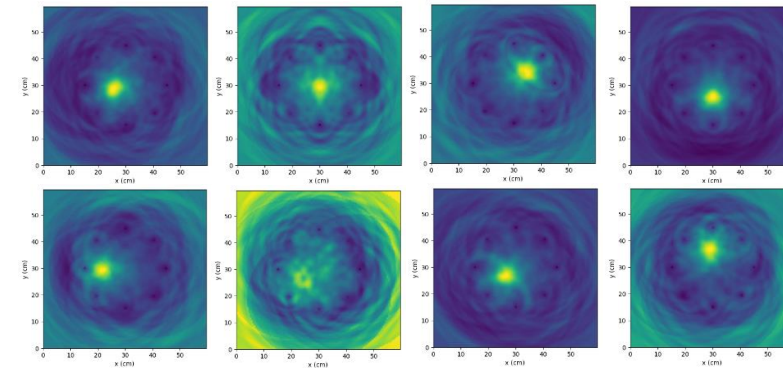


- Design of a CNN architecture



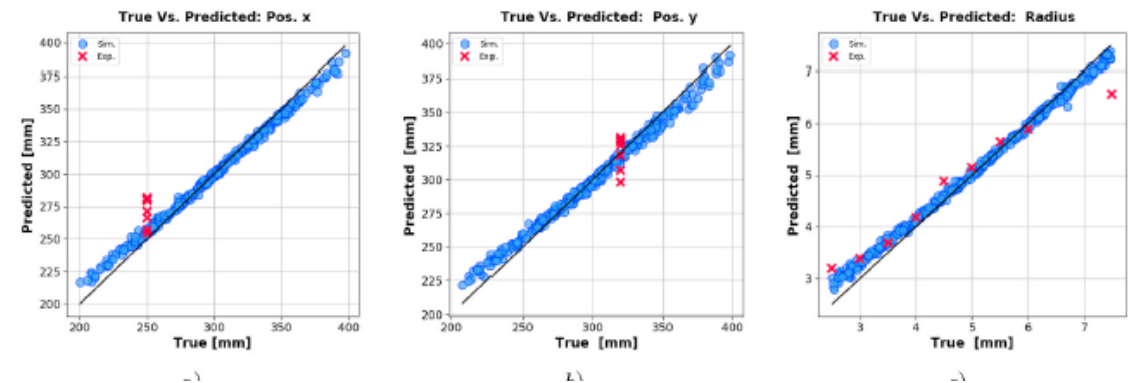
Miorelli, R., et al. "Defect sizing in guided wave imaging structural health monitoring using convolutional neural networks." *NDT & E International* 122 (2021): 102480.

- Creation of a training data set (LHS, 500 simulated images)



- Inversion results

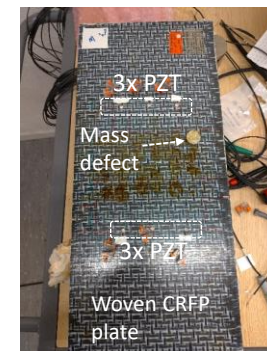
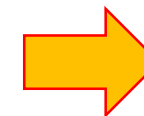
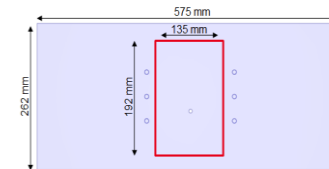
X Experiment
• Numerical



Fairly good results on location and size of holes (8 sizes 1 position)

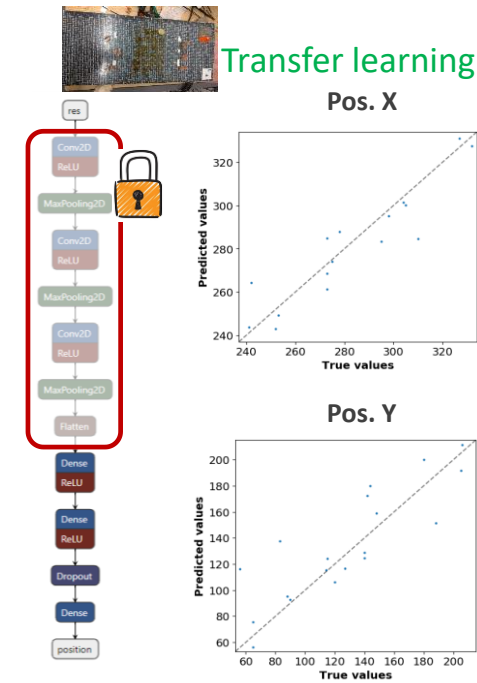
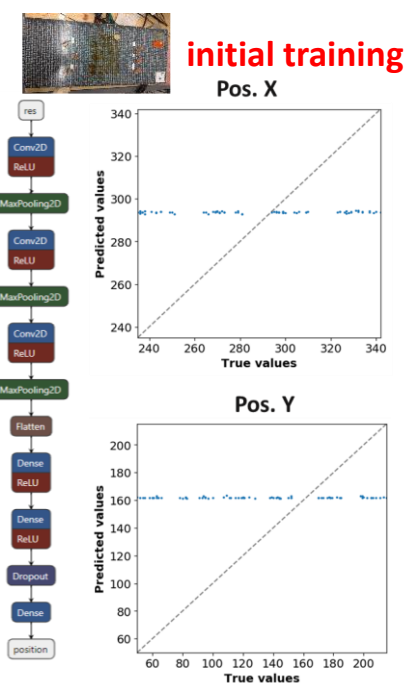
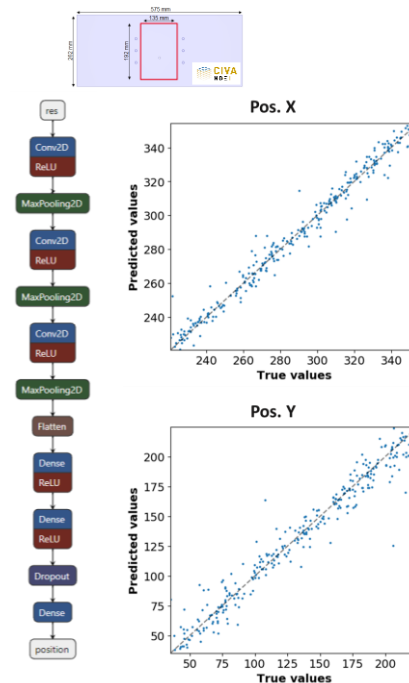
Current study : To apply this concept to a real-life complex case (woven CFRP)

Challenge: Simulation being computationally very demanding
Lack of representative set of simulations.



Investigated solution:

- The application of **transfer learning strategy** :
- Training on a **large number of cheap-to-compute but unaccurate** GW signals (simulation in Al plate)
- Training on a **small amount of highly accurate data** (3D FEM simulations in CFRP or experiments)
- **Assumption:** Sufficient similarity so that first layers can be transferred from Al to CFRP



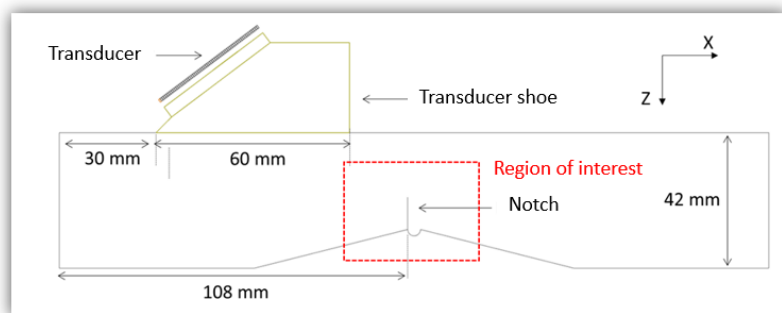
Transfer learning enables inversion accuracy based on a **small subset of experimental measures** available



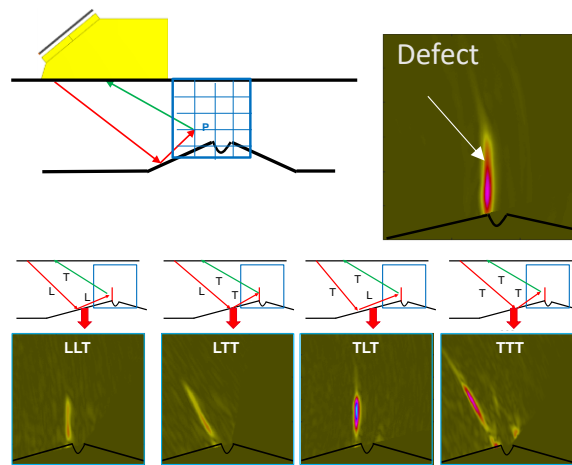
Sizing of defect detected by ultrasonic TFM imaging

Objective: Characterizing flaws (size and orientation) ultrasonic imaging (multimodal TFM) despite **uncertain knowledge of the piece geometry** and material acoustic celerity

➔ That means to assist an expert facing images not directly interpretable (artifacts, erroneous locations, etc.)

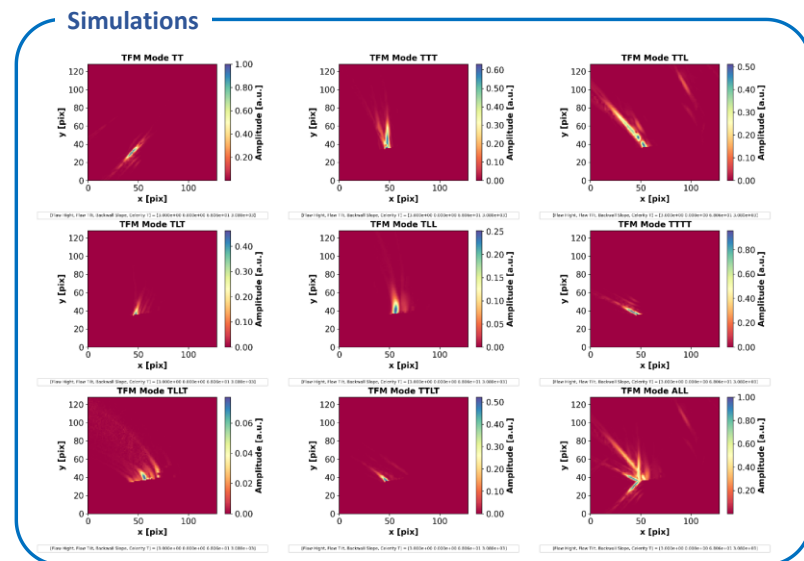


Configuration of interest
OT 55°, 64 elts, 5 MHz



Multimodal TFM images

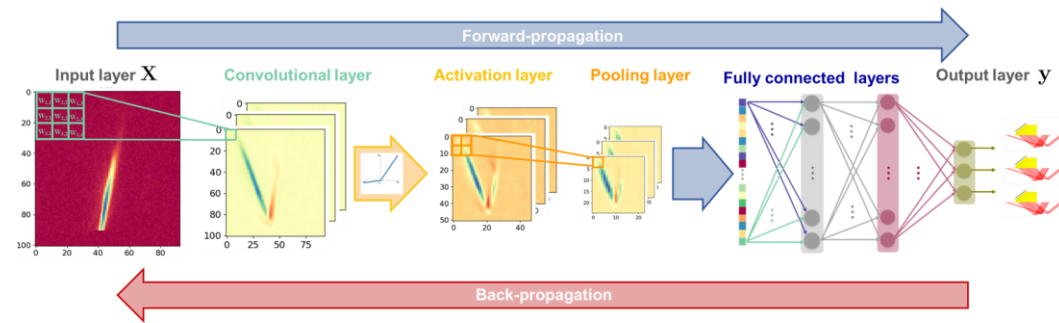
- Exploit the different acoustic paths
- Direct image of the defect
- Assume an accurate knowledge of TOF



Simulation of TFM images
reconstructed under uncertainties

Sizing of defect detected by ultrasonic TFM imaging

■ Design of a CNN architecture

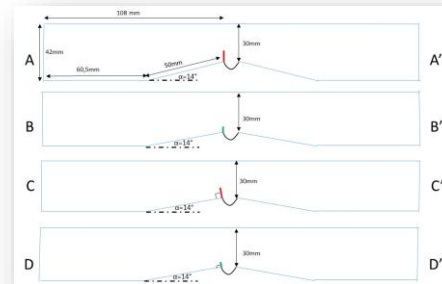


X Experiment
• Numerical

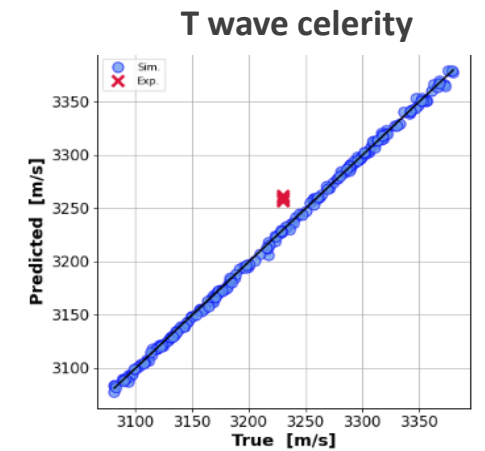
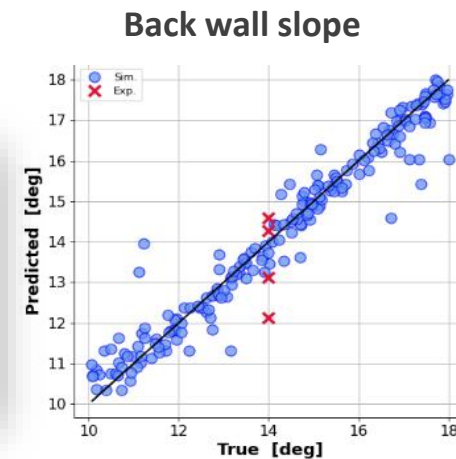
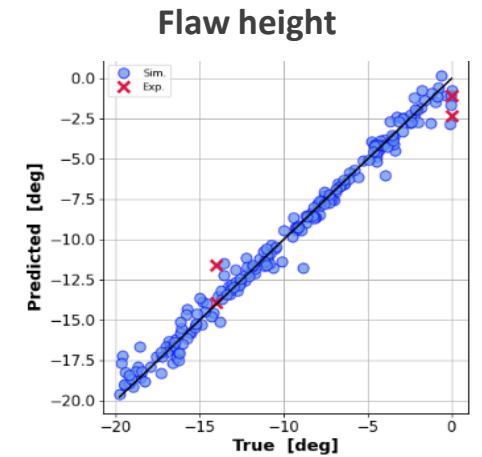
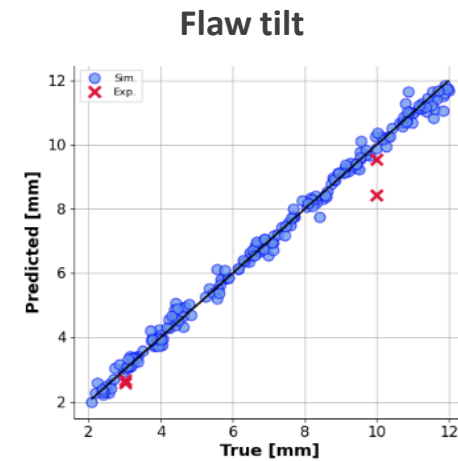
■ Creation of a training data set by CIVA

Dataset parameters	
Parameters	Var. Range
Flaw height [mm]	[2.0 , 12.0]
Flaw tilt [deg]	[-20, 0]
Backwall slope [deg]*	[10, 18]
Celerity T-waves [m/s]*	[3030, 3380]

One mock-up
with 4 defects



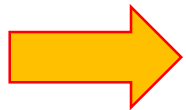
■ Inversion results



The design of an AI for NDE Diagnostic requires:

- NDE expertise
- Access of machine learning techniques
- Tools to generate (if simulated) or import data base and tools to process data (extraction of relevant criteria, reduction of data)
- Tools and data to assess the performances of the diagnostic

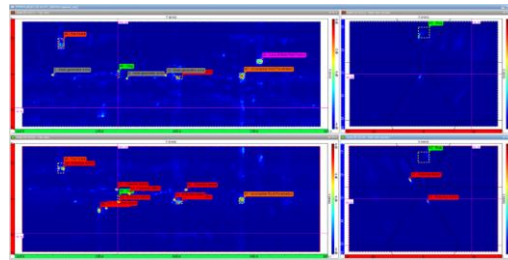
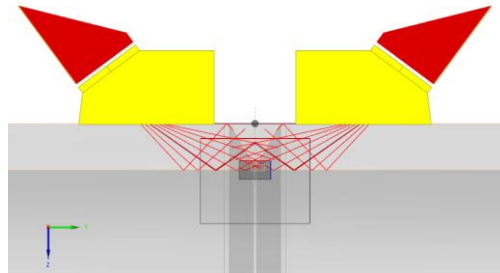
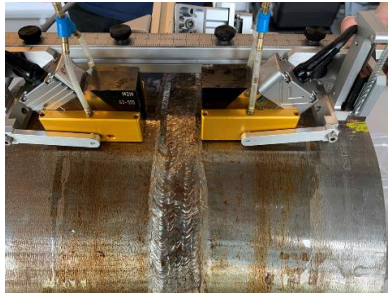
Beyond training of ML, **simulated database can be highly beneficial** at the different steps of the design of AI for diagnostic: Features engineering, features extraction, selection and evaluation of classifiers...



Development of a new module of CIVA, **CIVA DS** in order to make AI more accessible to the NDE engineer and to use simulation as a facilitator. Compatibility both with simulated and experimental dataset.



Use case



Weld inspection.

2 PA Probes : 5MHz 64 elements
TFM-PWI, 43° to 79°, 6 angles

Objective of the study : To design an AI able to detect and categorize defects. Evaluation by comparison with the inspection report provided by an expert.



Creation of data-base (simulation + exp)

- Feature engineering
- Features extraction, reduction of data
- Design of a classifier
- Evaluation on experimental data



Inspection report provided by the expert

NDE INSPECTION REPORT

ULTRASONIC

Customer	CEA Saclay	Date	28/03/19
Specimen ID	P-28163	Specimen Type	Pipe
Dimensions	25 THK. x 300 DIA.	Acceptance Spec.	SL08/88

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	Root Crack	28	493	-2	70
5	Incomplete Root Penetration	18	709	+10	70
6	Lack of Side Wall Fusion	15	766	+11	60
7	Porosity	24	845	+14	70/60

Comments: Misalignment noted.

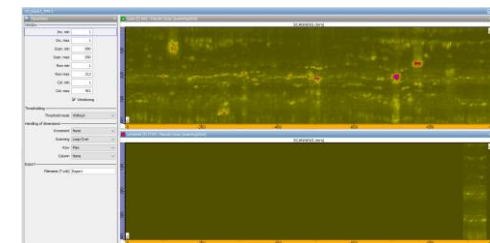
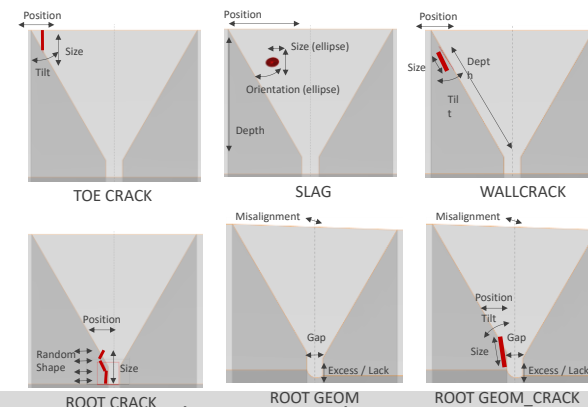
Inspector: Sam Berriman | Signed:

Defaut n°	Gate	Type	Amax signal(dB)	ΔY-dB	Y signal (max)	Y-min -dB	Y-max -dB	Z signal (max)	X signal (max)
A	(B1)	Inner geometric echo	-8,9	6	98	96	102	25,49	0,59
1	(B2)	Toe Crack	-7	19	120	116	135	50,03	-17,11
	(B1)	Toe Crack	-7	7	120	116	123	50,03	-17,11
I	(B2)	WALL CRACK	-10,4	16	124	119	135	49,59	-16,96
	(B2)	WALL CRACK	-7,7	10	133	127	137	49,15	-17,11
2	(B2)	WALL CRACK	-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
	-	Slag	-8,3	5	311	309	314	13,73	-1,62
3	(B1)	Slag	-8,3	4	311	309	313	13,73	-1,62
	(B2)	Slag	-9,6	4	312	310	314	10,94	1,77
D	(B2)	Potential defect	-5,3	7	313	309	316	31,66	1,77
	(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
	-	Incomplete Root Penetration	-0,6	15	706	703	718	21,08	0,88
5	(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

Detection and identification of indications (6 types of defects)

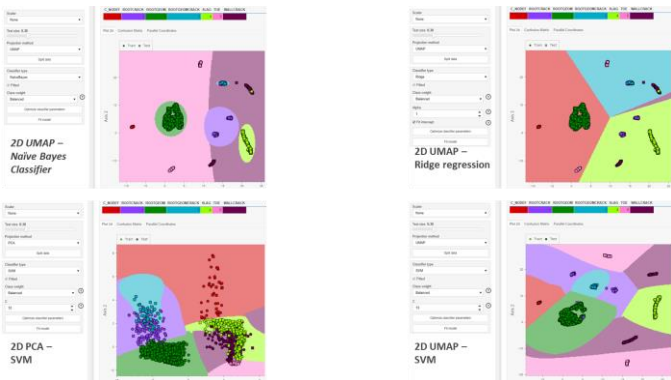
Simulations : variations of position and size for the 6 classes of defects

Training set for « no defect » : Import in CIVA DS from experimental files

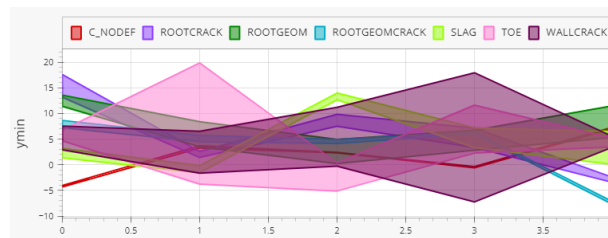


Reduction of data + design of the classifier :

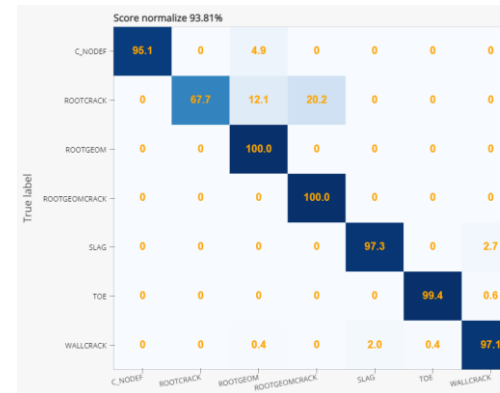
- Inspired by NDE expertize: choice to keep the 2 **echodynamic on TFM images** which should contain the « signature » of the defect
- Evaluation of different algorithms : Features extraction + classifier



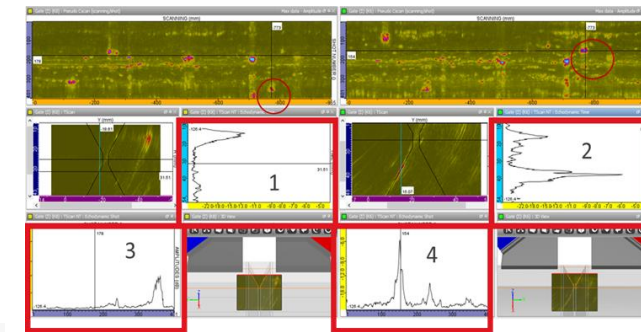
Comparison ≠ extractions and classifiers



UMAP 5D for entire learning dataset



Confusion Matrix (SVM - UMAP 5D)

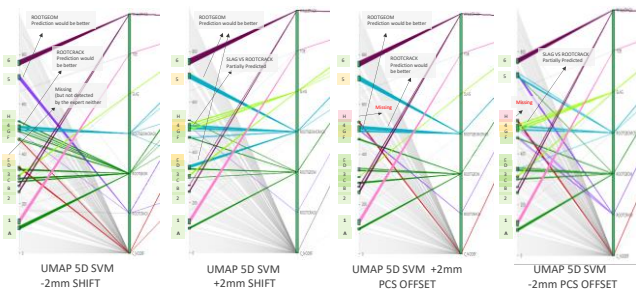


Example of WALLCRACK defect on experimental data



Final choice:
UMAP 5D and SVM

Confrontation with experiment:



Default n°	Gate	Type	Amax signal (dB)	ΔV -6dB	Ysignal (mm)	Y - min (mm)	Y - max (mm)	Z signal (mm)	X signal (mm)
A	(B1)	Inner geometric echo	-6,9	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
I	(B1)	Toe Crack	-10,4	16	124	119	135	49,59	-16,96
	(B2)	Potential defect	-7,7	10	133	137	137	49,15	-17,11
2	(B2)	Wallcrack	-5,7	7	250	246	253	35,78	6,05
	(B2)	Wallcrack	-10,2	5	272	270	275	33,42	5,01
C	(B2)	Potential defect	-9	7	308	303	310	22,26	-5,31
	-	Slag	-8,3	5	311	309	314	13,73	-1,62
3	(B1)	Slag	-8,3	4	311	309	313	13,73	-1,62
	(B2)	Slag	-9,6	4	312	310	314	10,94	1,77
D	(B2)	Potential defect	-5,3	7	313	309	316	31,66	1,77
	(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
	(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
	-	Slag	-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
	-	Incomplete Root Penetration	-0,6	15	706	703	718	21,08	0,88
5	(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
	-	Lack of Side Wall Fusion	-5,7	17	771	760	777	37,83	-7,37

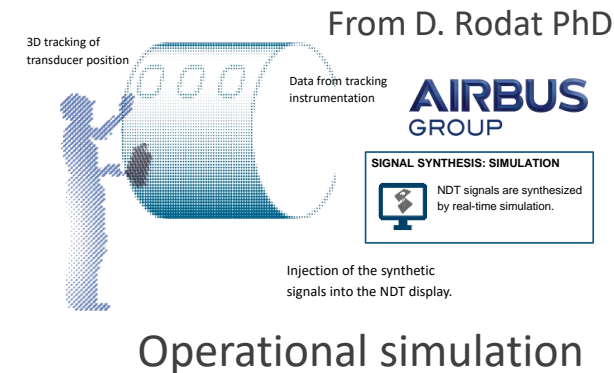
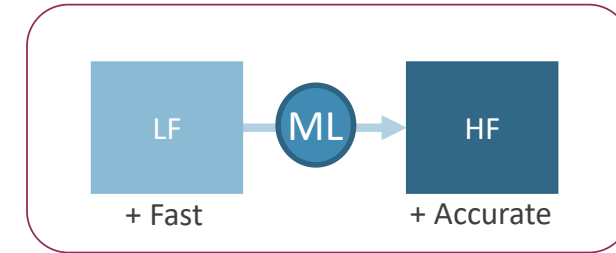


Convincing comparison with expert analysis:

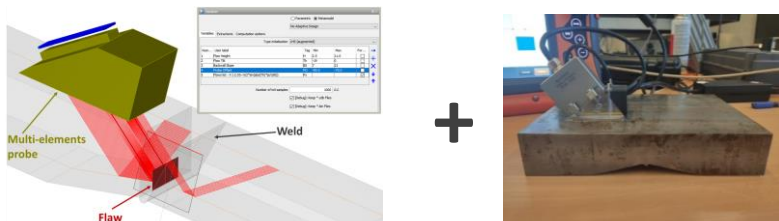
- All referenced defect are detected and correctly classified
- but one non referenced indication (H) is not detected

Current research directions

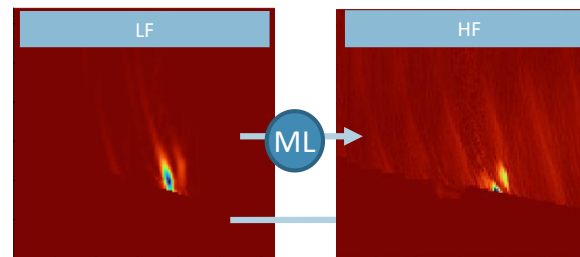
- There is no « perfect » model: Physics based models capture only a part of the reality.
- Multi-fidelity generative models can be built from low fidelity and high fidelity data
- Can be used to improve models:
 - Learn components not or incorrectly taken account by the model (noise, image texture) and **make simulated and experimental data indistinguishable for an operator.**
 - Possible application: Generation of realistic synthetic signals in representative on-site conditions for a more complete integration of **Human factors in POD studies**
 - To « augment » the capability (domain of application or accuracy) of simplified models** (fast but unaccurate) by learning from high fidelity model (accurate but heavy).



Multimodal TFM + uncertainties



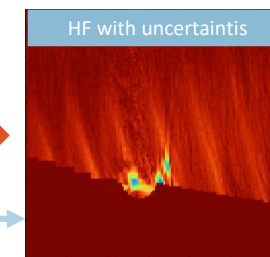
Example of same realisation: **simulation** and **experience** TFM reconstruction parameters without uncertainties



From G. Granados PhD works

Same experimental realisation with **uncertainties on the geometry** of the piece (same flaw geometry, etc.)

Example of the impact of uncertainties on the TFM images



- NDE simulation and AI are definitely complementary: Simulation for AI & AI for simulation.
- General agreement on the generation by simulation of synthetic training data-sets.
- At this stage only proofs of concept which have to be validated/consolidated on a case by case basis
- Challenge: How to deal with the unavoidable gap between simulation and reality ?
- Different solutions can be investigated:
 - Increase the accuracy of forwards model eventually using AI (mixed physics-data driven models);
 - Increase the robustness of AI : Hybrid data-set, transfer learning, preprocessing of data ...
- Strong benefit expected to bring together in a same environment: NDE expertise, simulation data handling/analysis and AI tools.



Thank you for your attention