DE LA RECHERCHE À L'INDUSTRIE

Metamodels and Statistical Tools Applied to Non-destructive Testing Problems

UQSay #12, Online Seminar, 09 July 2020, **Roberto MIORELLI[1]**, Christophe REBOUD[1] , Pierre CALMON[1]

[1]CEA-LIST, Department of Imaging and Simulation for NDT,

Gif-sur-Yvette, France

OUTLINE

Part 1: R&D for Non-Destructive Testing (NDT) at CEA LIST

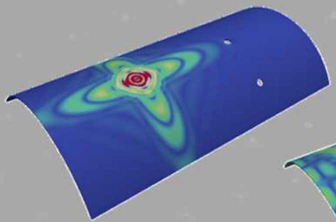
- Quick presentation of CEA LIST and its NDT department
- Non-destructive testing the industrial context, the R&D and the challenges

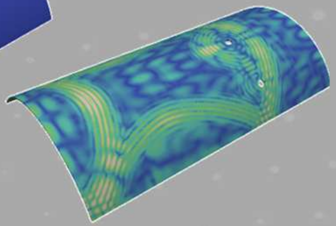
Part 2: Model driven approaches for NDT applications

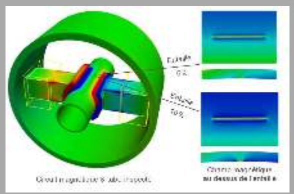
- Industrial context and motivation
- Dataset generation applied to forward and inverse problems
- Ultrasound Testing (UT) fast iterative optimization under uncertainties
- Eddy Current Testing (ECT) classification tasks in steam generator tubes
- Structural Health Monitoring (SHM) inspection based on ultrasound guided wave imaging

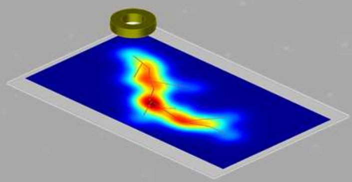
Part 3: Wrapping up

- Conclusions, remarks and what’s next



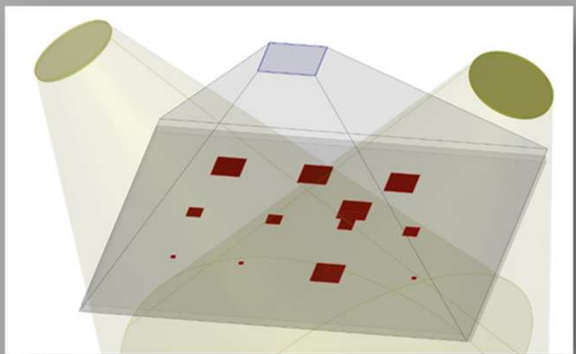






Part 1

R&D activities on Nondestructive testing at CEA LIST



R&D FOR NON-DESTRUCTIVE TESTING AT CEA LIST

Quick presentation of CEA LIST and its NDT department

19 975 employees
1 351 PhD students and Postdoctoral fellows

9 centres

Cadarache *(nucléaire fission, fusion, propulsion, nouvelles technologies de l'énergie)*
Cesta *(architecture et garantie des têtes nucléaires, Laser MégaJoule)*
DAM Île-de-France *(physique des armes nucléaires, simulation numérique, lutte contre la prolifération nucléaire et le terrorisme, ingénierie, Très Grand Centre de Calcul, Centre d'alerte aux tsunamis)*
Gramat *(vulnérabilité des systèmes d'armes et efficacité des armements)*
Grenoble *(nouvelles technologies pour l'énergie, la santé, l'information et la communication, nanosciences, cryogénie, biosciences et biotechnologies)*
Le Ripault *(matériaux non nucléaires pour la dissuasion, pile à combustible, stockage de l'hydrogène),*
Marcoule *(nucléaire : cycle, déchets)*
Paris-Saclay *(nucléaire, climat et environnement, sciences de la matière, recherche technologique, sciences du vivant et de la santé)*
Valduc *(matériaux nucléaires pour la dissuasion, installation radiographique Epure)*

5 **regional platforms for technological transfert**

Nantes, Bordeaux, Toulouse, Metz, Lille

Nuclear and Renewable Energies

Fundamental Research

Technological Research

Defense and Security

4 Institutes

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Département Imagerie Simulation pour le Contrôle (**DISC**)

About 100 people, 85% of the funding coming from industrial and collaborative projects

R&D FOR NON-DESTRUCTIVE TESTING AT CEA LIST

Quick presentation of CEA LIST and its NDT department

- Missions: develop innovative NDT technologies (simulation, instrumentation, techniques) and transfer them to industry (platforms CIVA NDE, GERIM 2, SACHEM)

- About 100 people, more than 85% of the funding coming from industrial and collaborative projects

- Various NDT methods studied: Ultrasounds, Electromagnetics, X-ray, Thermography, Structural health monitoring

- Strong links with national and international academic community: CIVAMONT project

Non-destructive testing the industrial context, the R&D and the challenges

Embedding simulation tools in NDT devices

Real time imaging and post-processing

Sensors design

Flexible array probes

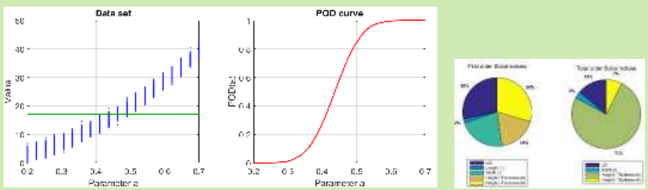
Development of imaging and reconstruction techniques

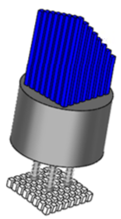
Characterization and diagnosis

Inversion, image processing, machine learning methods

Reliability assessment

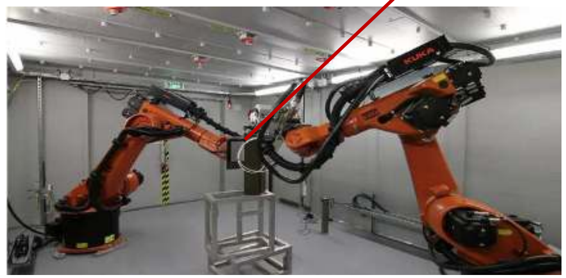
Management of uncertainties, model assisted POD (MAPOD)

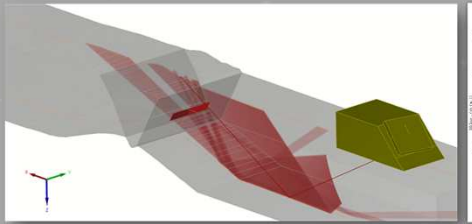


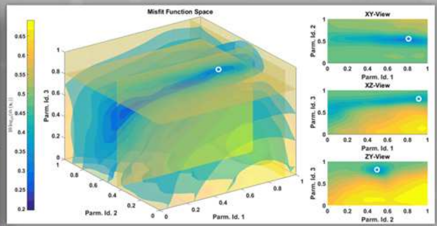


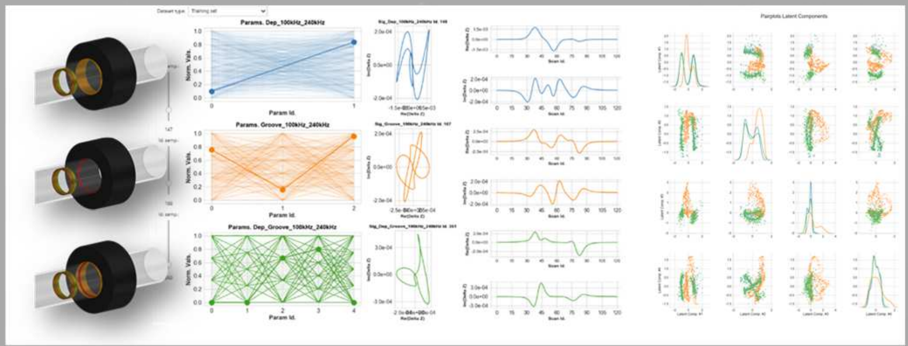
New NDT and SHM methods

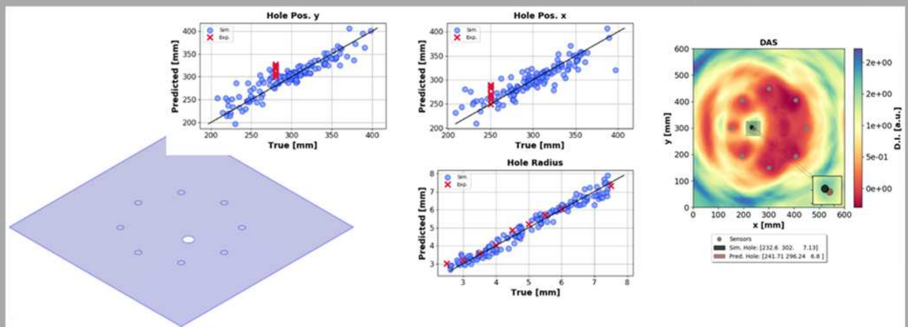
Robotized NDT inspection of complex materials, SHM











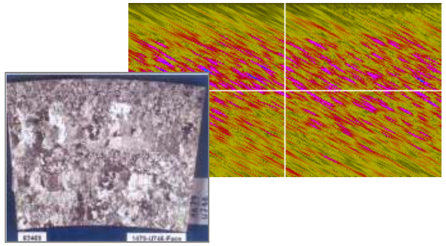
Part 2

Model driven approaches for NDT applications

Industrial context and motivation

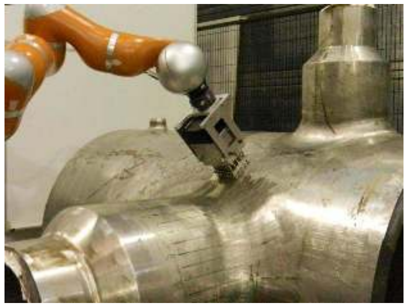
Model driven approach objectives

- Material characterization (advanced manufacturing)
- Inputs for diagnosis, lifetime prediction
- Demonstration of performance
- Probes optimization
- ***Flaw(s) detection, classification and characterization***



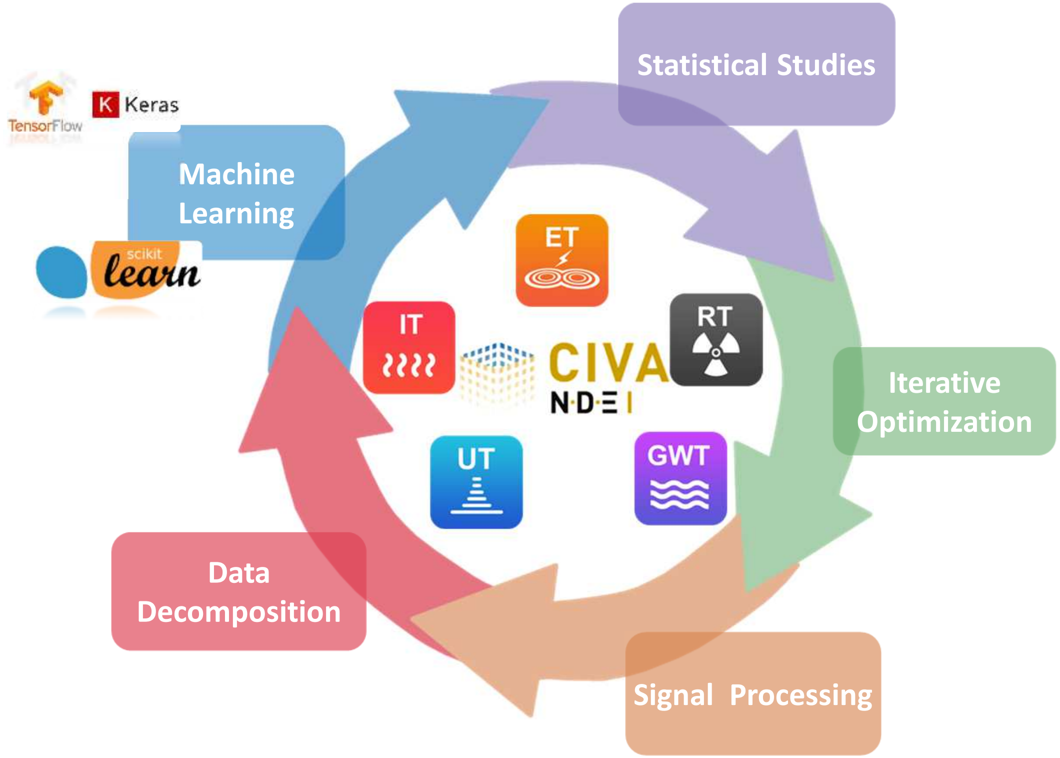
Flaw(s) detection, classification and characterization

- Sizing
- Shape / type (criticality)
- Confidence bounds on the estimation
- Well-posedness of the inverse problem
- Fast inversion (online diagnosis)



MODEL DRIVEN APPROACHES FOR NDT APPLICATIONS

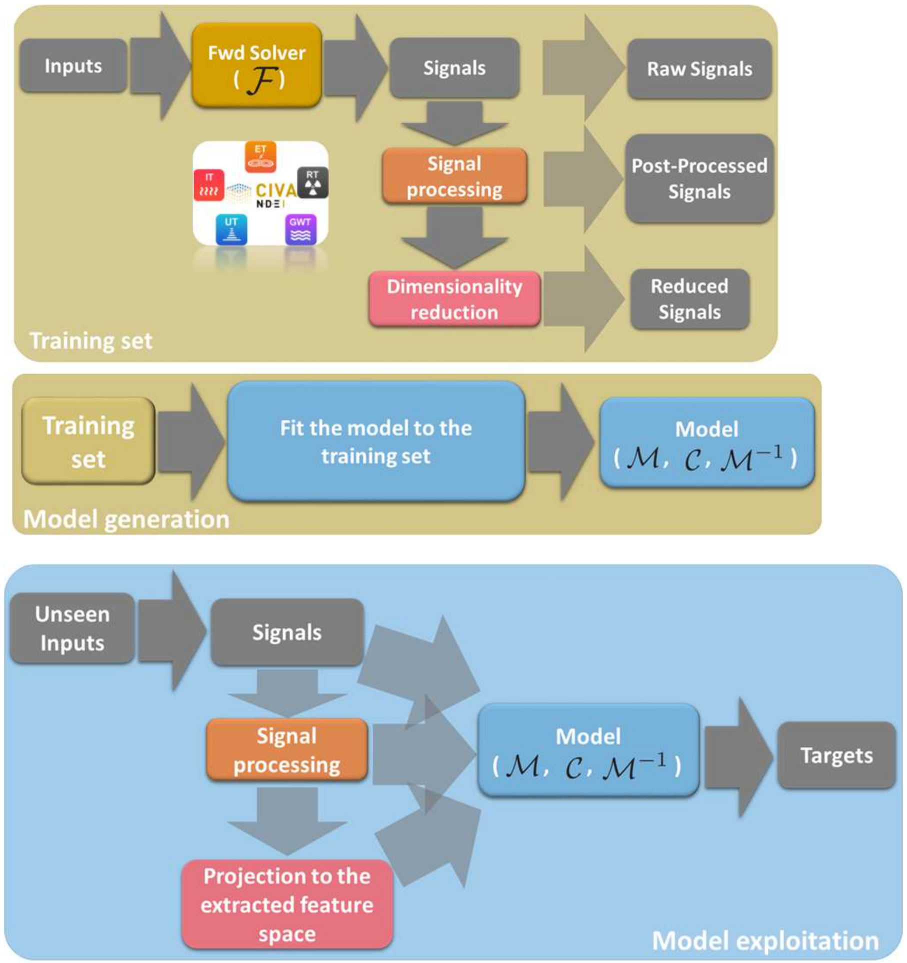
Dataset generation applied to forward and inverse problems



- **Machine learning approaches for regression and classification tasks**
- **Dimensionality reduction and feature extraction for raw signal compression and dataset generation**
- **Signal processing of raw signals targeting a given NDT task**
- **Iterative optimization for parameter estimations targeting failure(s) localization and characterization, and probe optimization**
- **Statistical studies e.g., POD, sensitivity analysis assessment, uncertainties propagation, etc.**

- **Design specific tools** to tackle meaningful NdT problems in effective way (e.g., NdT-engineers)
- **Enhance CIVA to a general, flexible, modern and collaborative platform** to share developments with partners (e.g., industrial and academic projects)
- **Integration** of “worthy” developments within CIVA

Dataset generation applied to forward and inverse problems



Signal processing

- Imaging methods (mostly employed for UT, GWI and tomographic RX problems)

Dimensionality reduction/Manifold learning

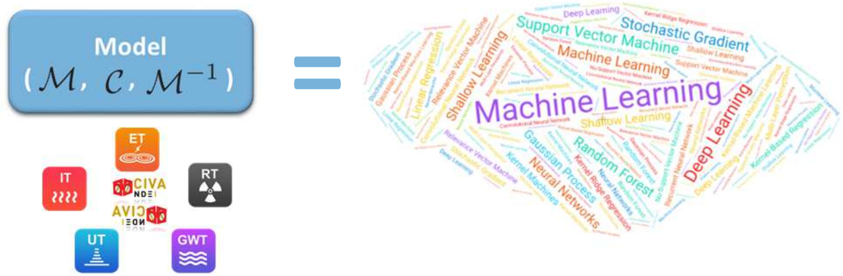
- Unsupervised linear methods (PCA, etc.)
- Supervised linear methods (PLS, CCA, etc.)
- Unsupervised non-linear methods (Kernel-PCA, Isomap, etc.)

Classification models

- **Kernel machines:** GPC, SVM, etc.
- Ensemble-methods: decision trees, random forests, etc.
- **Deep architectures:** MLPC, CNN, etc.

Regression models

- **Shallow architectures (aka kernel machines):** KRR, SVR, GPR, etc.
- **Deep architectures:** MLPR, CNN, RNN



Dataset generation applied to forward and inverse problems

1. Database/training set generation

Design of Experiment (DoE): a priori definition of the sampling configurations

- ✓ Deterministic sequence (Full Factorial design, list of values, etc.)
- ✓ Pseudo-random sequences (Latin Hypercube Sampling, Sobol's and Halton's sequences, etc.)

Adaptive database sampling schemes with Output Space Filling (OSF) [Bil2010]

- ✓ Meshless approaches
- ✓ Mesh-based approach

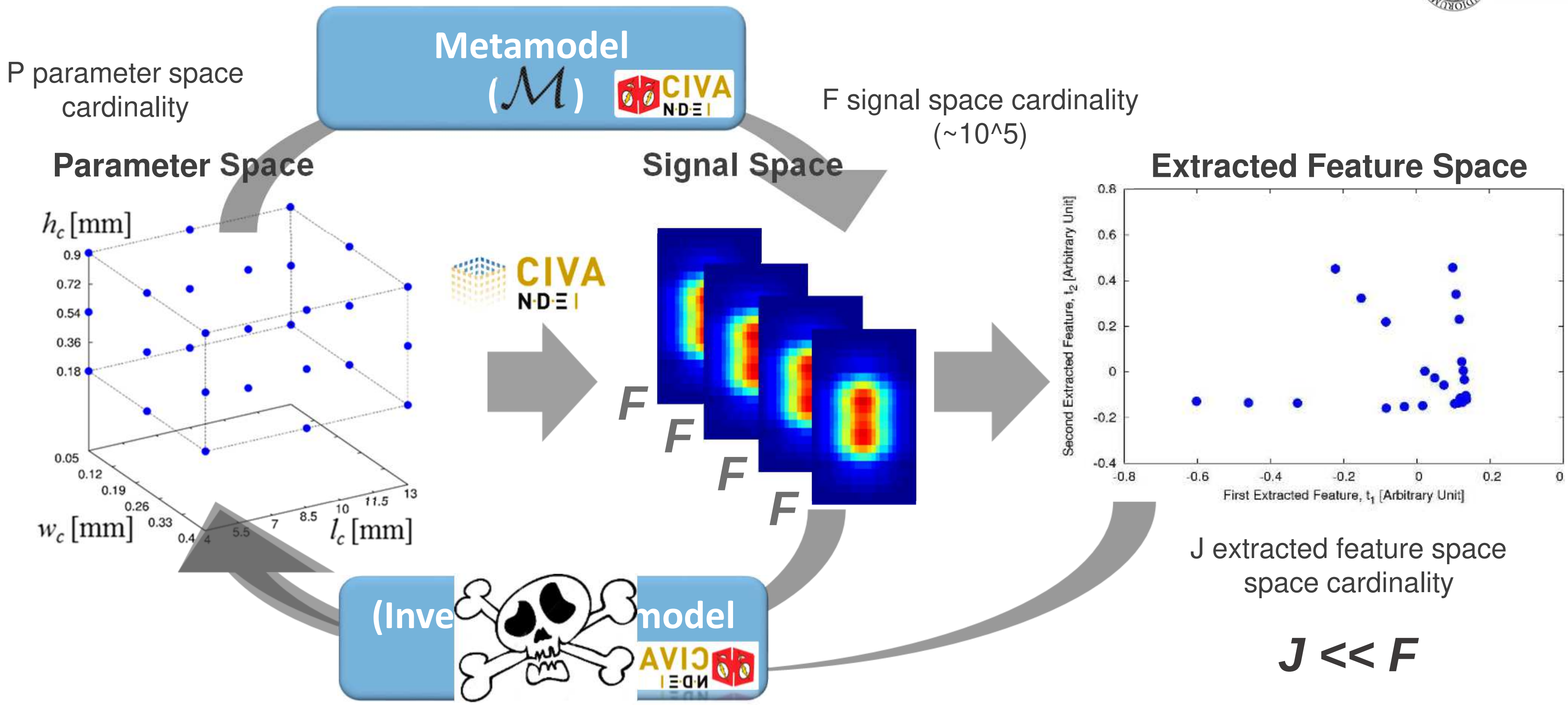
Adaptive database sampling schemes with Feature Space Filling (FSF) [Sal2016]

- ✓ Meshless approaches

2. Creation of the model

Kriging (a.k.a. Gaussian process regression)
Radial basis function
Kernel ridge regression
Support vector machine
Multilinear interpolator
Deep learning (Multilayer perceptron, convolutional neural network, etc.)
…

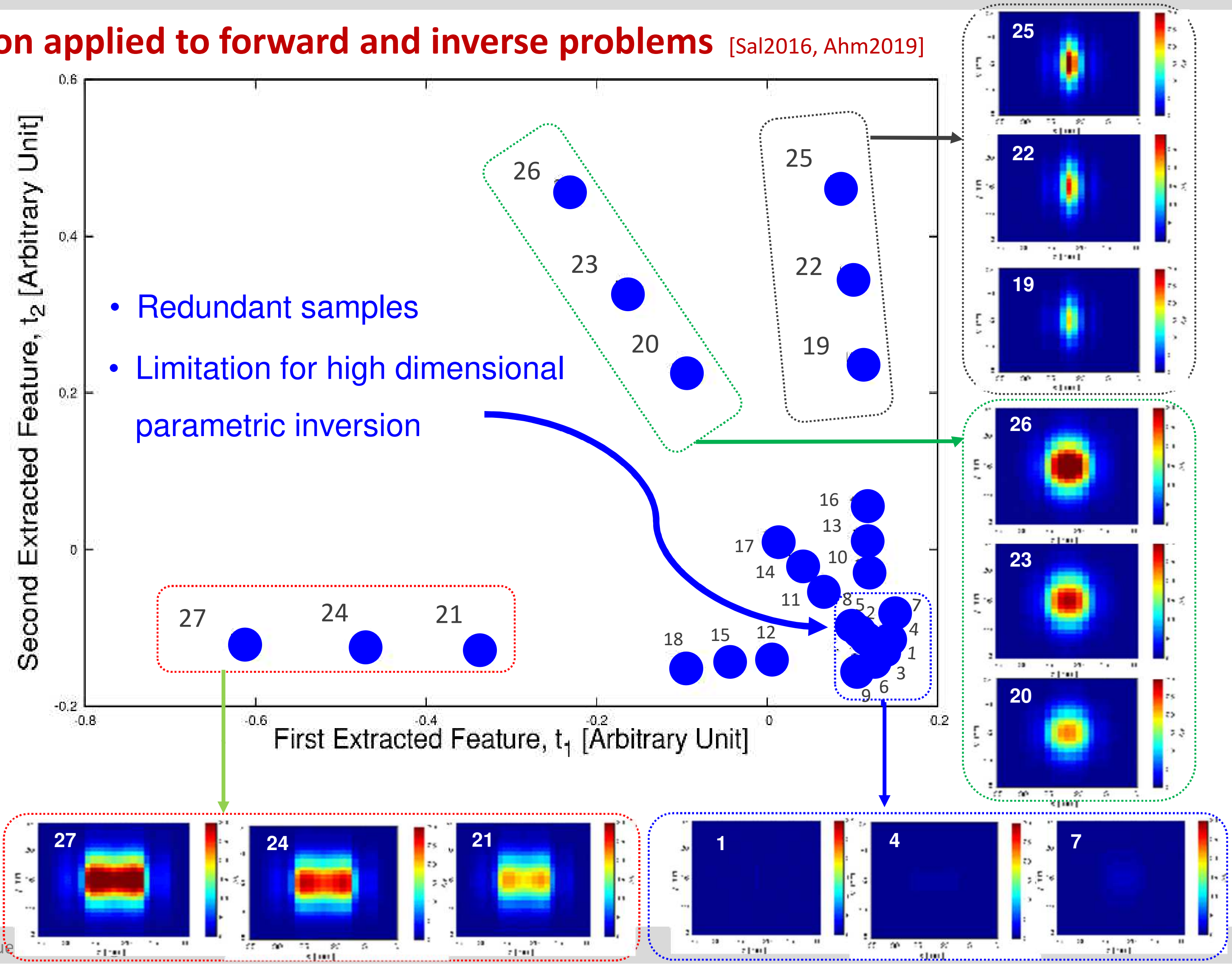
Dataset generation applied to forward and inverse problems [Sal2016, Ahm2019]



F ↑ → # of samps. N ↑↑

→ Curse of dimensionality

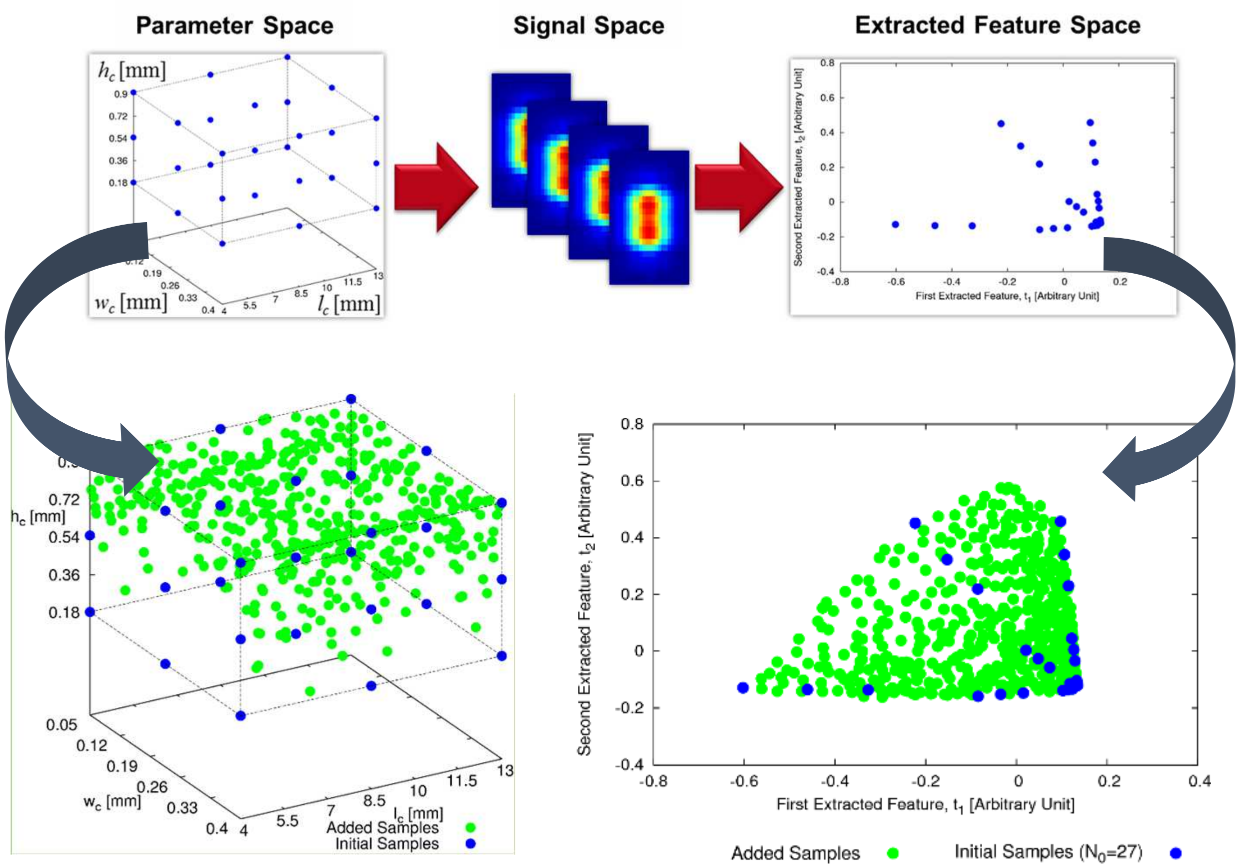
Dataset generation applied to forward and inverse problems [Sal2016, Ahm2019]



How to improve sampling performance?

Dataset generation applied to forward and inverse problems [Sal2016, Ahm2019]

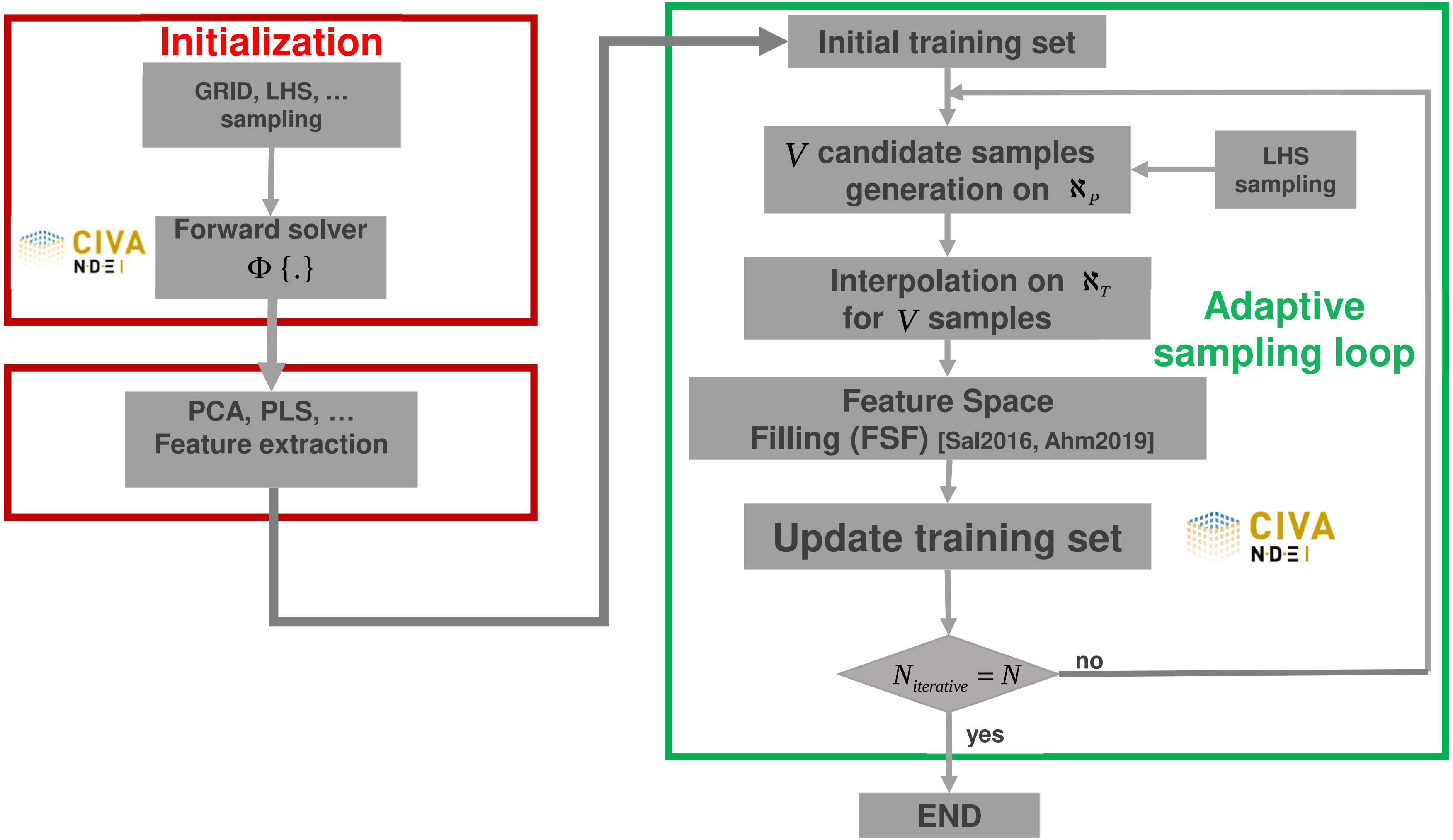
Adaptive sampling on the extracted feature space



Parameter space is sampled by filling extracted feature space uniformly

- **Increases learning ability** → the most informative samples are accounting
- Suitable for **high dimensional problems**
- Higher prediction accuracy for **lower *N***

Dataset generation applied to forward and inverse problems [Sal2016, Ahm2019]



Ultrasound Testing (UT) fast iterative optimization under uncertainties

What do uncertainties represent?

- ✓ Human factor (changes in probe lift-off, trajectory, etc.)
- ✓ Aging of probes (changes in electrical components, materials, etc.)
- ✓ Non-homogeneity/Non-conformity of probes (different manufacture)
- ✓ Specimen tolerances (welds, bending effects, material characteristics, etc.)
- ✓ Inspection conditions (temperature, etc.)

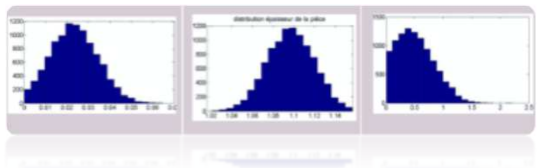
How to propagate uncertainties within the inversion process

1. Split the parameter space into uncertain parameters and unknown ones
2. Associate a pdfs to uncertain parameters
3. Propagate uncertainties by means of the metamodel
4. Perform inversion

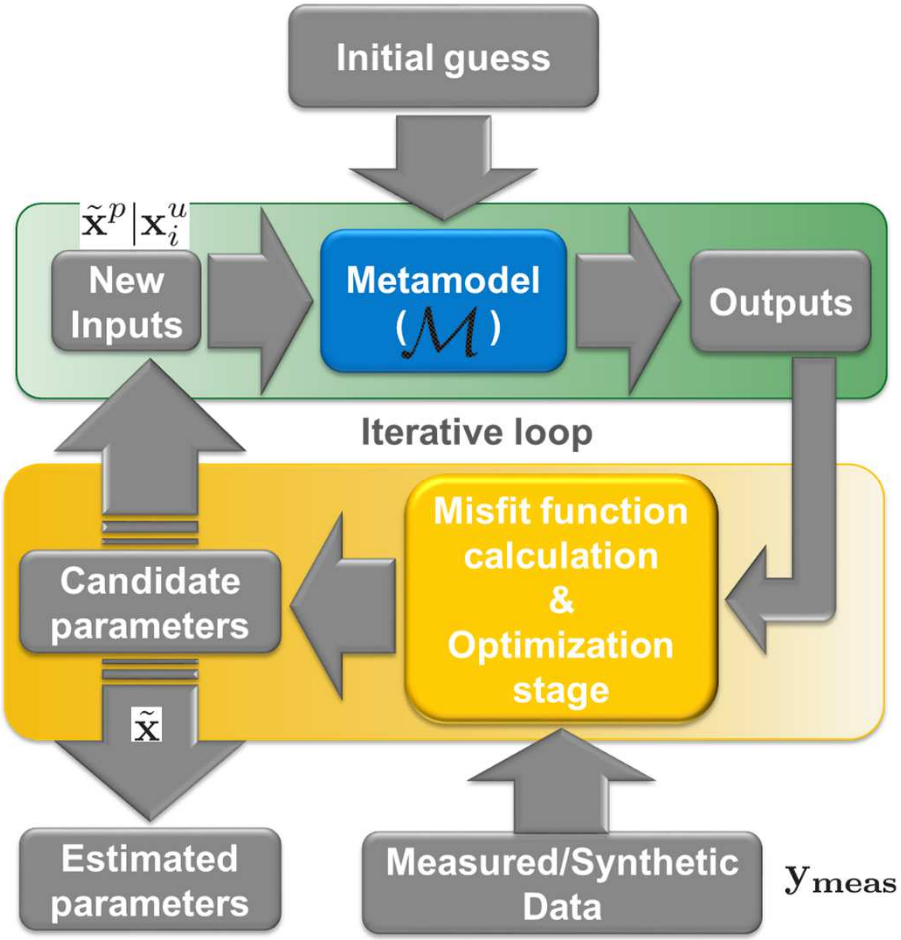
$$\mathbf{x}_i = [x_1, ..., x_{D-U}] \cup [x_1, ..., x_U] = \mathbf{x}_i^p \cup \mathbf{x}_i^u$$

Set of values *D-U* inputs

Statistic “uncertain” distribution on *U* inputs



Ultrasound Testing (UT) fast iterative optimization under uncertainties

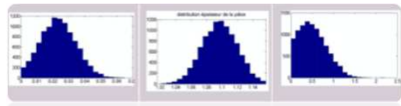


- Inputs

$$\mathbf{x}_i = [x_1, ..., x_{D-U}] \cup [x_1, ..., x_U] = \mathbf{x}_i^p \cup \mathbf{x}_i^u$$

Set of values *D-U* inputs

Statistic “uncertain” distribution on *U* inputs



- Misfit function with uncertainty propagation

$$\hat{m}(\mathbf{x}_i^p|\mathbf{x}_i^u) = \|\mathbf{y}_{\mathbf{meas}} - \mathcal{M}\{\mathbf{x}_i^p|\mathbf{x}_i^u\}\|_2^2$$

- Optimization algorithms
  - Stochastic (MCMC, evolutionary strategies, etc.)
  - Deterministic (derivative-based, derivative-free, etc.)

$$\tilde{\mathbf{x}} = \arg\min_{\mathbf{x}_i^p \in X} \hat{m}(\mathbf{x}_i^p|\mathbf{x}_i^u) \quad \tilde{\mathbf{x}} \in \mathbb{R}^{1\times(D-U)}$$

Ultrasound Testing (UT) fast iterative optimization under uncertainties

Probe and specimen parameters

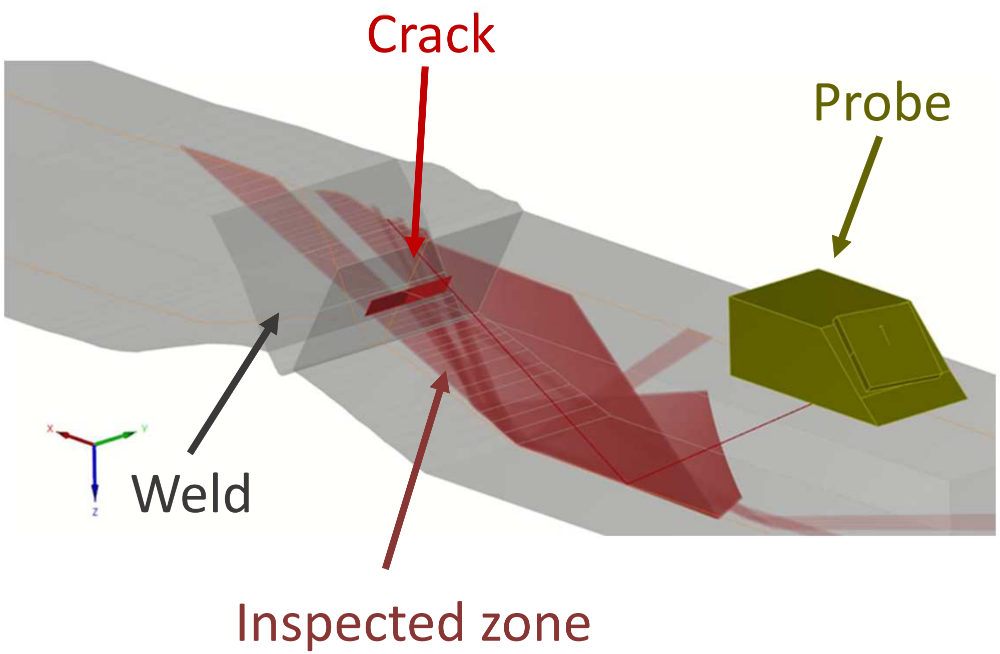
Parameters	
Signal Central Frequency [MHz]	2
Specimen Thichkness [mm]	42.062
Weld Angle [deg]	120

Inversion algorithms

Matlab fmincon [Mat12] Quadratic Programming (QP) nonlinear programming methods	Num. iter max. = ~170
Differential Evolution (**DE**) [Pri05]	Pop size = 105 ind. Num. iter max. = 70

Database & metamodel main parameters

Database/Metamodel Types.	Adaptive A-RBF / A-RBF
Number of total samples	3500
No. of measured feature (per sample)	65559



[Mat2012] Matlab 2012b, Optimization Toolbox™
[Pri2005] Price et al, Differential Evolution, A Practical Approach to Global Optimization, Springer, 2005

Ultrasound Testing (UT) fast iterative optimization under uncertainties

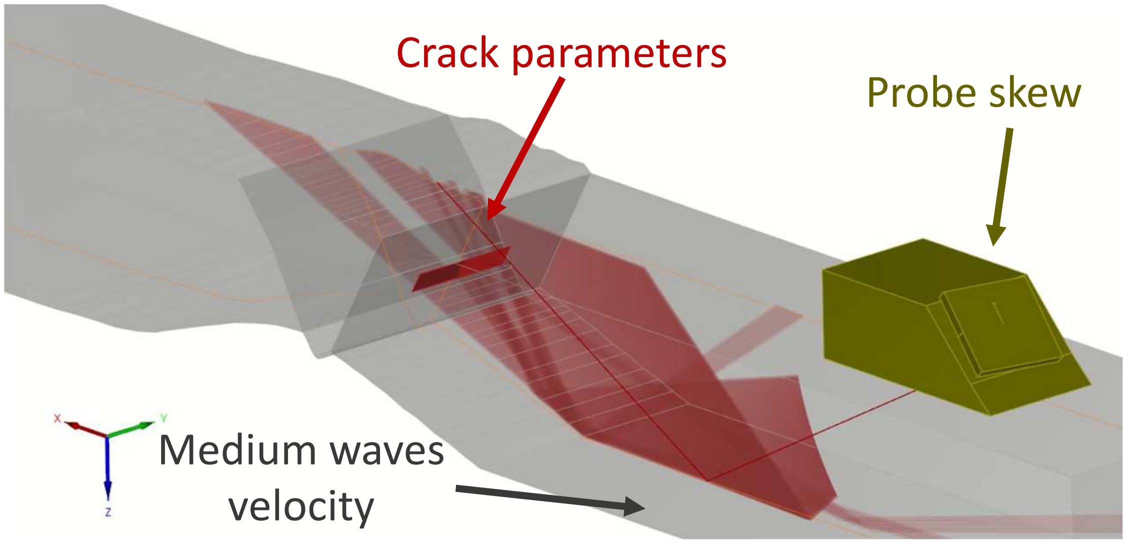
UT test case: flaws characterization and localization nearby weld bevel in 2D-extruded CAD geometry

Uncertain parameters

Parameters	Var. Range
Probe Skew [deg]	[0, 15]
Medium Waves Velocity [m/s]	[3180, 3280]

Defect parameters

Id.	Flaw Param.	Var. Range
1	Height [mm]	[2, 6]
2	Length [mm]	[8, 26]
3	z-Position [mm]	[11, 25]



- Synthetic Additive White Gaussian Noise (AWGN) corruption

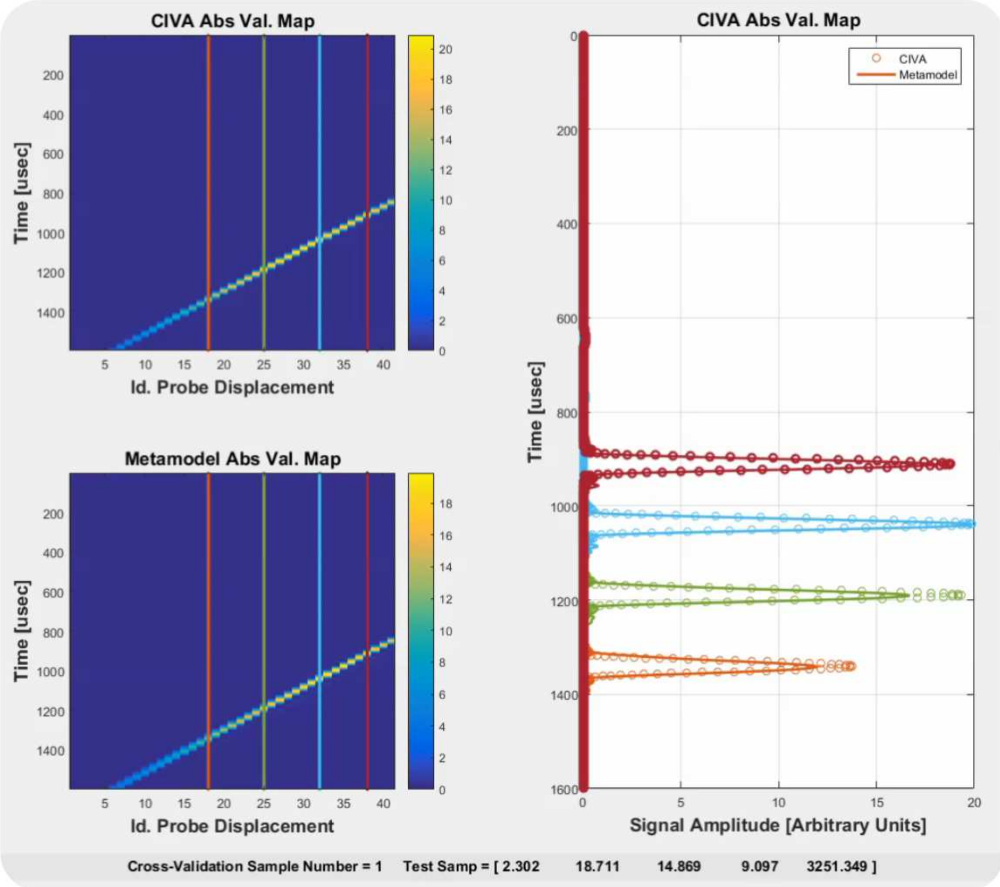
$$SNR_{\mathrm{dB}} = 10 \log \sum_{i=1}^{K} \frac{|A_i|^2}{|\sigma_i|^2}$$

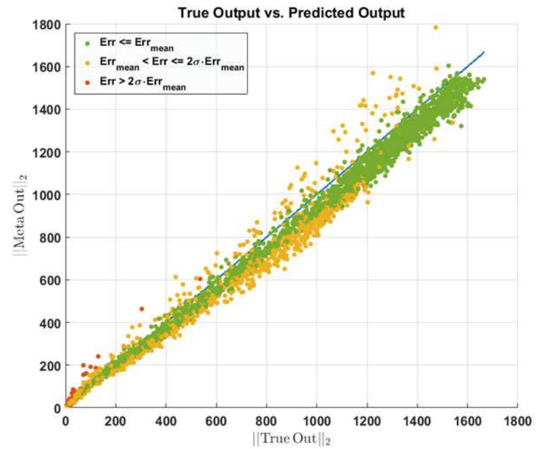
- Inversion prediction performance metric

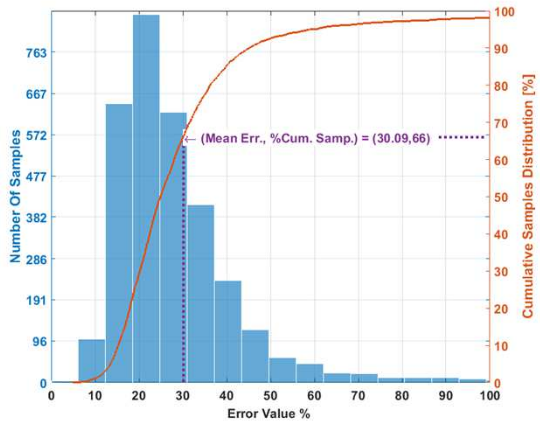
$$R^2 = 1 - \frac{\sum_{i=1}^{N} (x_i - \hat{x}_i)^2}{\sum_{i=1}^{N} (x_i - \overline{x})^2} \qquad NMSE = \frac{1}{N} \frac{\sum_{i=1}^{N} (x_i - \hat{x}_i)^2}{\overline{x} \cdot \overline{\hat{x}}}$$

Ultrasound Testing (UT) fast iterative optimization under uncertainties

UT metamodel validation through 10-k cross-validation

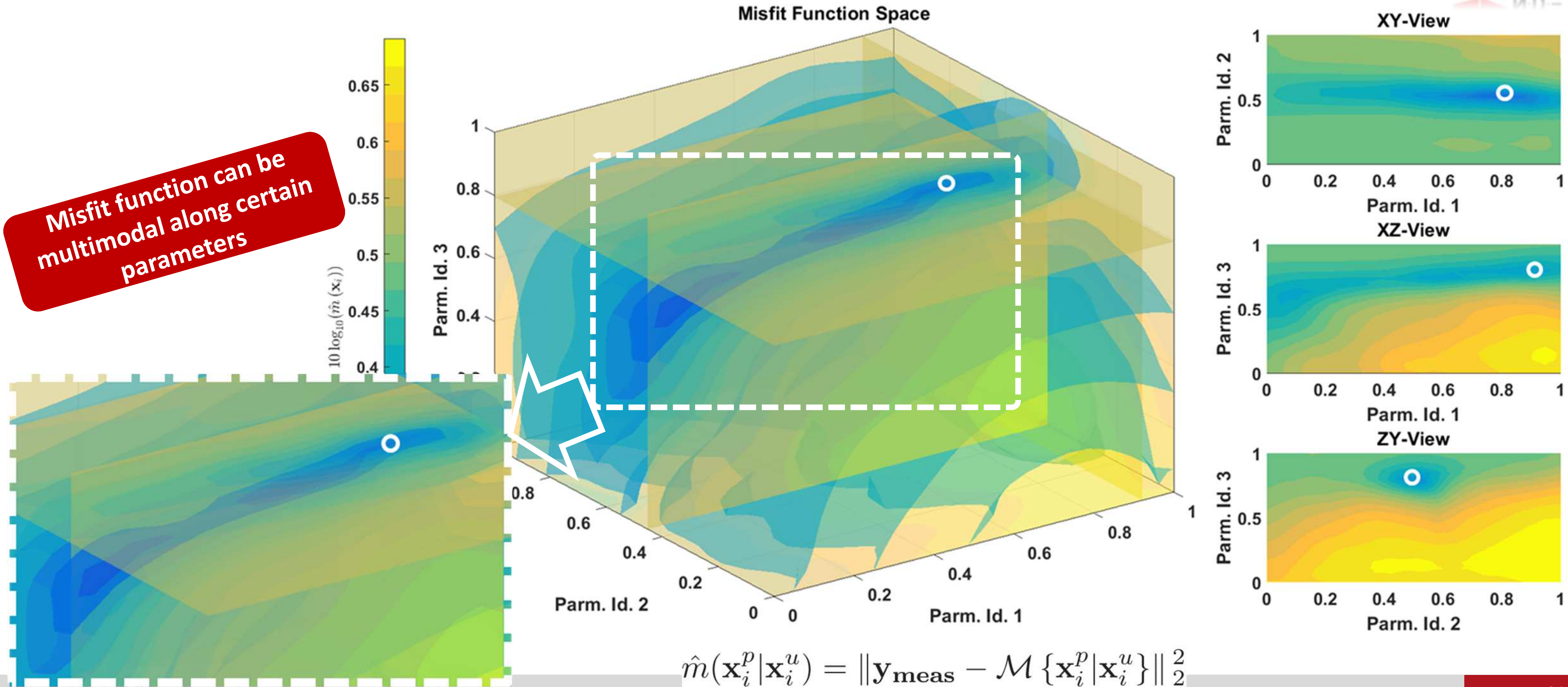






Ultrasound Testing (UT) fast iterative optimization under uncertainties

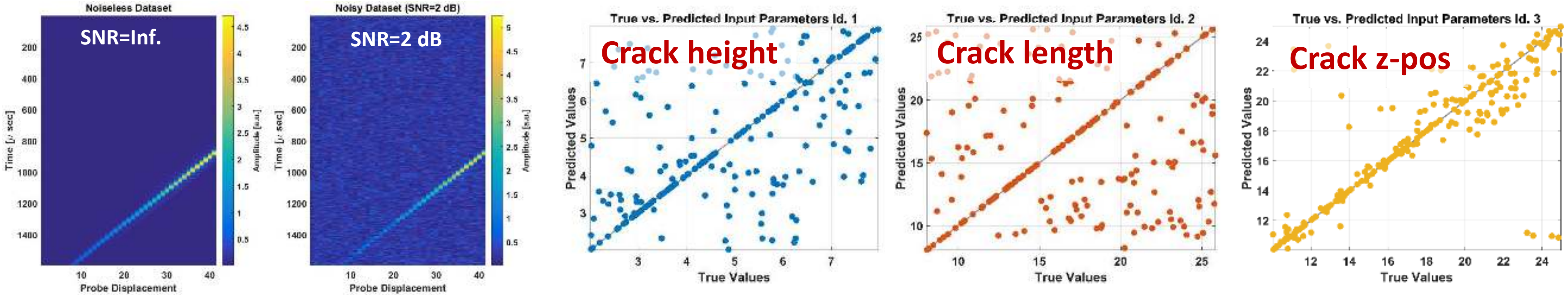
Example of ill-posedness of UT inverse problem (**no UQ**)



$$\hat{m}(\mathbf{x}_i^p|\mathbf{x}_i^u) = \|\mathbf{y}_{\mathbf{meas}} - \mathcal{M}\{\mathbf{x}_i^p|\mathbf{x}_i^u\}\|_2^2$$

Ultrasound Testing (UT) fast iterative optimization under uncertainties

QP and **DE** inversion results: study of the robustness **SNR = 2 dB** (AWGN) corruption (**no UQ**)

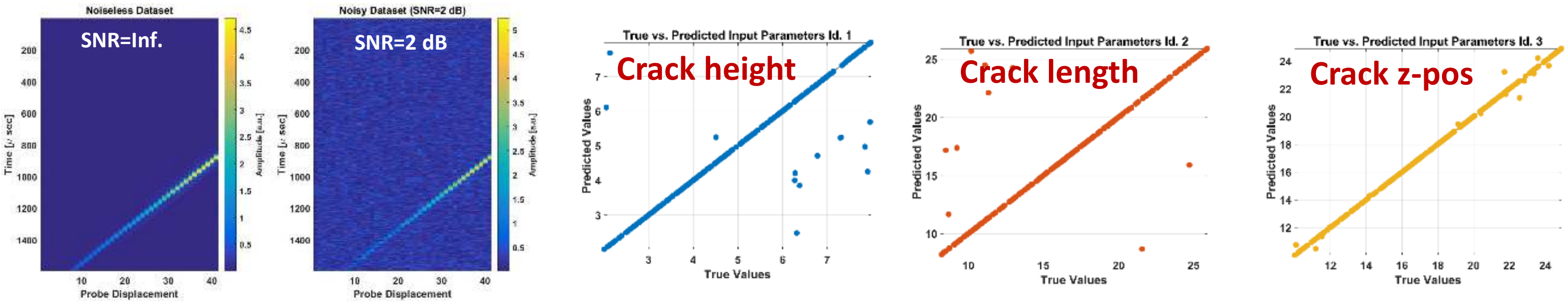


Param. Id.	1	2	3
R2	0.91	0.82	0.99
NMSE	0.15	0.17	0.013

Average inversion time: **45 secs** (~170 metamodel calls)

Forward solver time: **~1 minute**

QP cannot predict param. Id. 1 and 2



Param. Id.	1	2	3
R2	0.99	0.99	1.0
NMSE	0.014	0.03	~1e-4

Average inversion time: **~180 secs** (~7k metamodel calls)

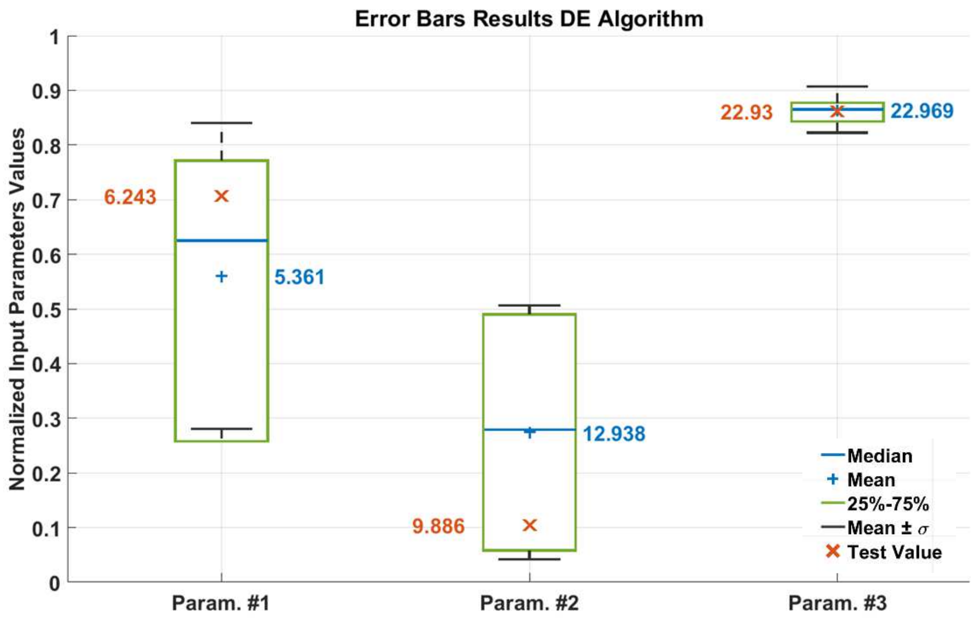
Forward solver time: **~1 minute**

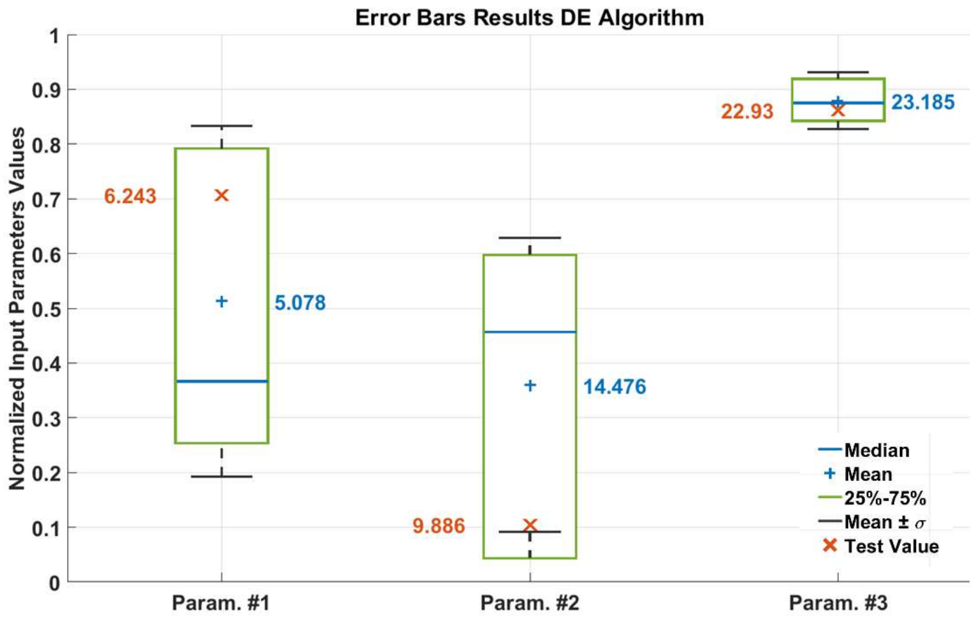
DE shown much few ouliers

MODEL DRIVEN APPROACHES FOR NDT APPLICATIONS

Ultrasound Testing (UT) fast iterative optimization under uncertainties

Effects of uncertainties (i.e., two PDFs) on predicted outputs (SNR = 2 dB) using DE algorithm



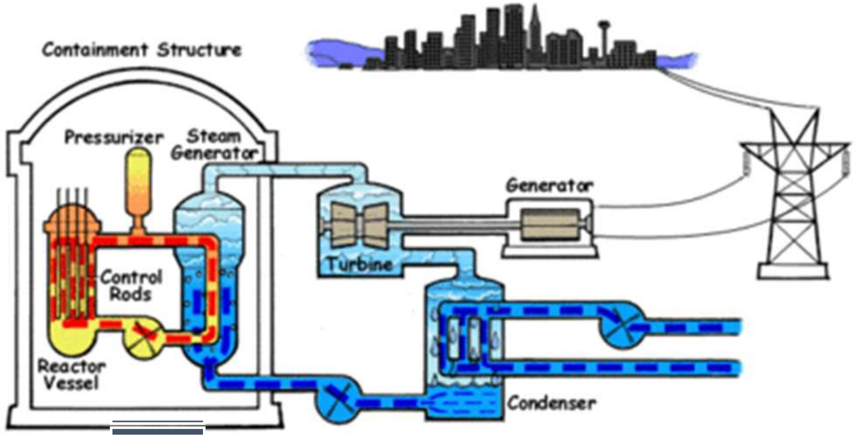


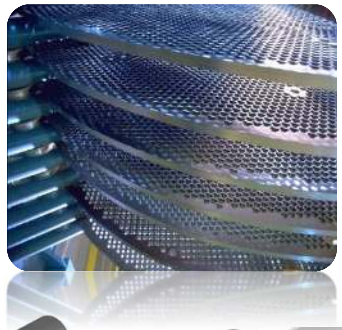
Norm. Param.	Pdf Laws
Probe Skew	N(μ, s^2) = [0.5, 0.15]
Medium Waves Velocity	U(a ,b) = [0.39, 0.61]

Norm. Param.	Pdf Laws
Probe Skew	N(μ, s^2) = [0.5, 0.15]
Medium Waves Velocity	U(a ,b) = [0.3, 0.7]

Uncertainties on inputs may impact hugely the predictions of crack for the crack height and length

Eddy Current Testing (ECT) classification tasks in steam generator tubes

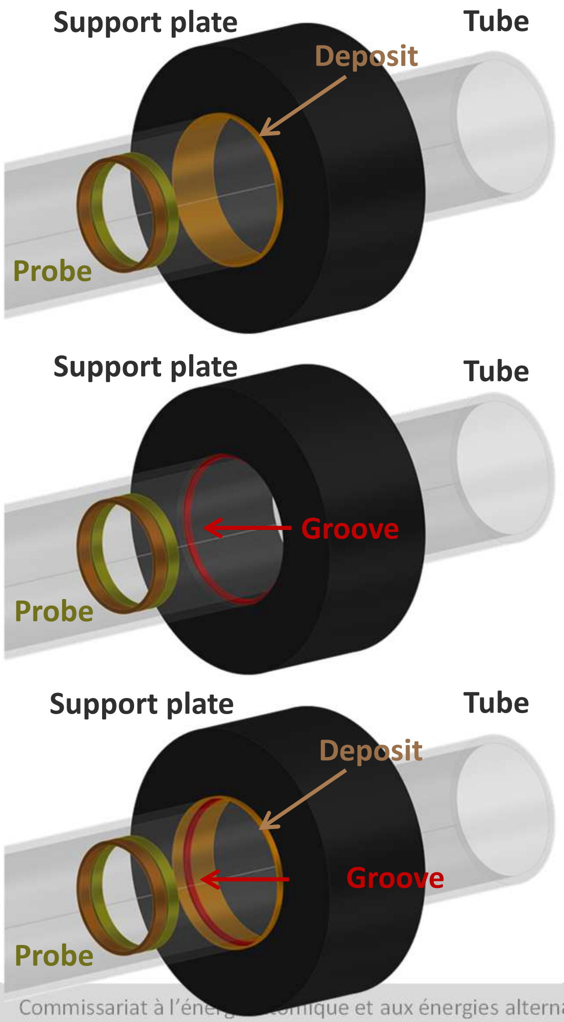


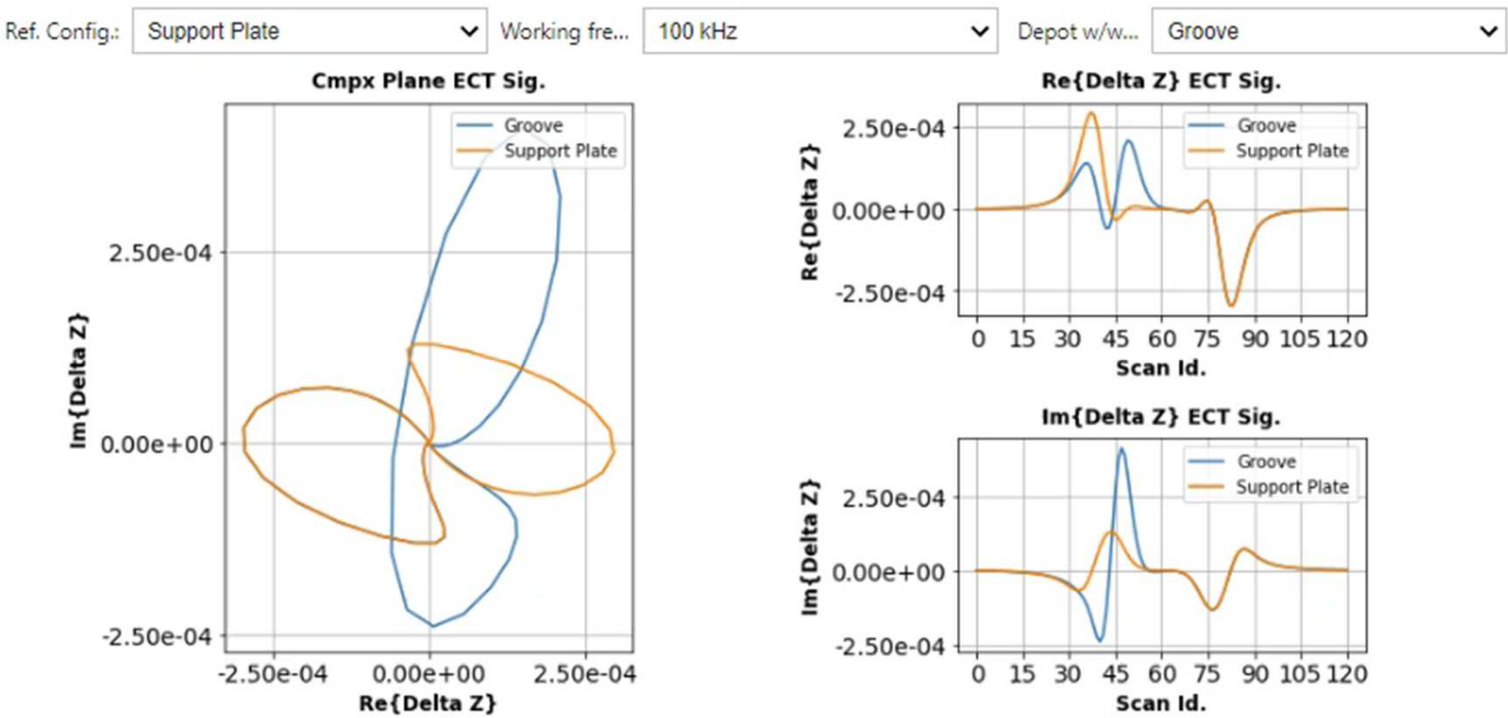


Inspection problem complexity of steam generator (SG) tubes

- Detection of flaws between support plates
- Detection of wall thinning nearby support plate
- **Discrimination between support plate, deposit (clogging) and flaw signals**

Eddy Current Testing (ECT) classification tasks in steam generator tubes





Important observations

- Variation of ECT signal due to the deposit is quite strong
- Perturbation of ECT signal due to small grooves is “hidden” by the deposit

Eddy Current Testing (ECT) classification tasks in steam generator tubes

Classification methods studied based on CIVA simulations

Objectives of the work

1. Establish a robust methodology for training a ML classifier based on synthetic signals
2. Assess the performance of the classifiers in view of performing automatic classification tasks

Supervised learning

- Training the ML algorithm with couples of inputs/targets generated via numerical solver

Classifiers studied

- Naive Bayes (NB)
- K-Nearest Neighborhood (KNN)
- Multilayer Perceptron Classifier (MLPC)
- Support Vector Classification (SVC) with Gaussian kernel

Dimensionality reduction technique

- Principal Component Analysis (PCA)

Eddy Current Testing (ECT) classification tasks in steam generator tubes

Problem definition

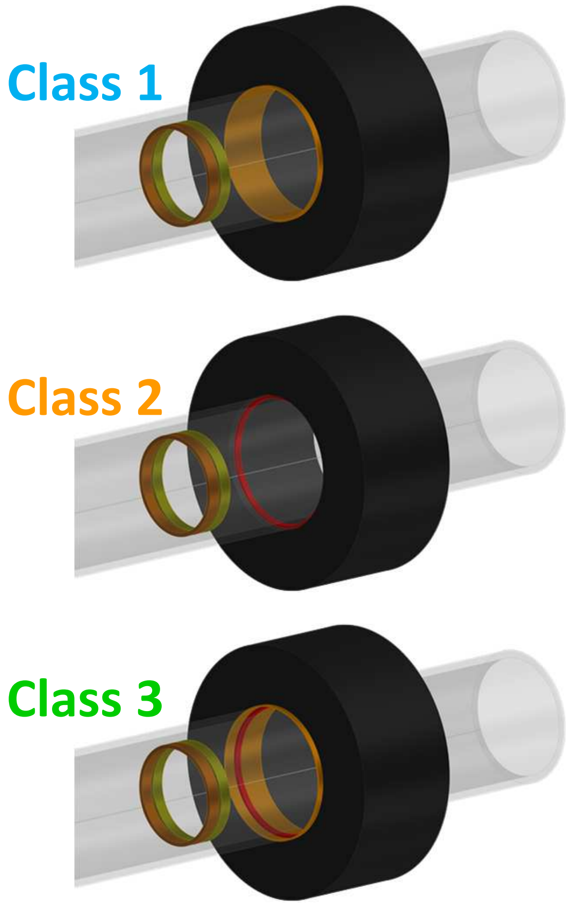
Addressed classes

Class Id.	Class Type
Class 1	Deposit only
Class 2	Groove only
Class 3	Deposit and Groove

CIVA NDE

Considered parameters

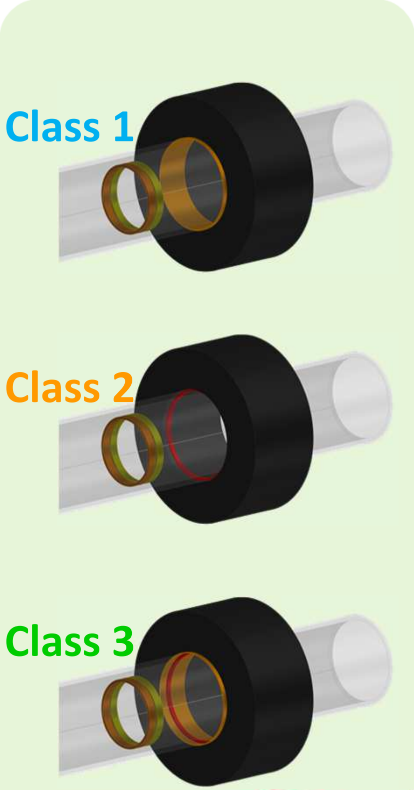
Id.	Flaw Parameters	Var. Range
1	Deposit thickness [mm]	[1e-2, 2e-1]
2	Deposit length [mm]	[2, 10]
3	Groove length [mm]	[0.5, 2.0]
4	Groove height [mm]	[0.127, 0.762]
5	Groove z-position [mm]	[65.5, 75]



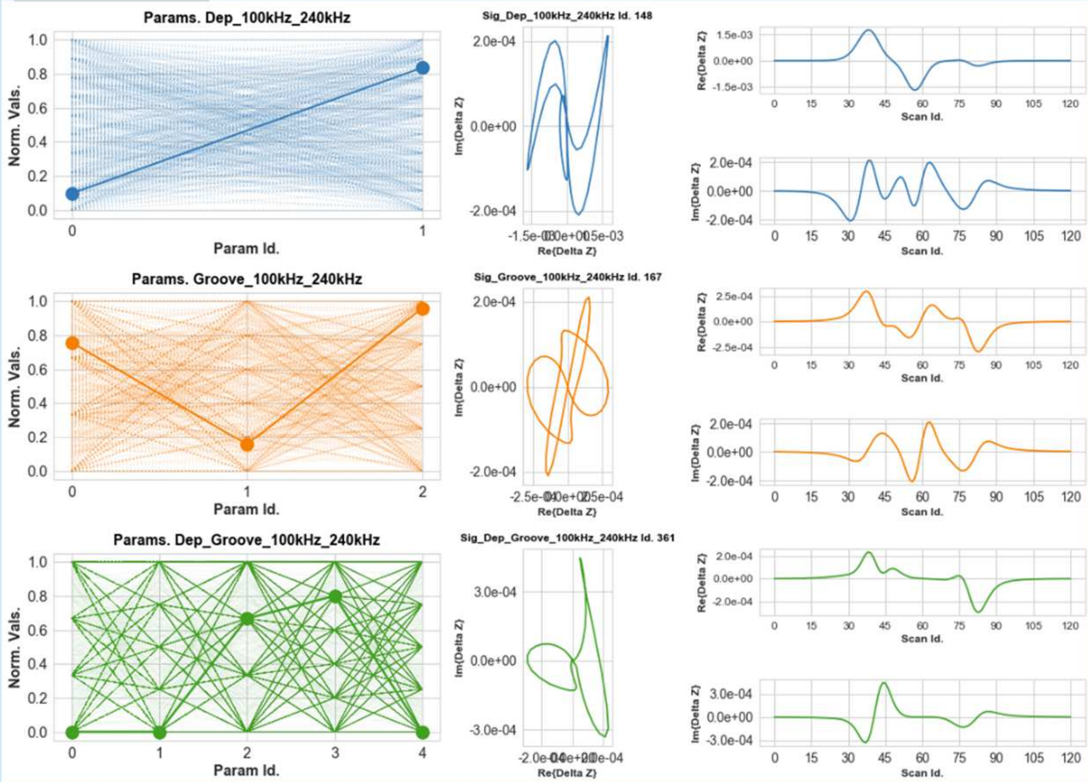
Eddy Current Testing (ECT) classification tasks in steam generator tubes

Offline phase: dimensionality reduction of ECT signals and learning stage of the classification model

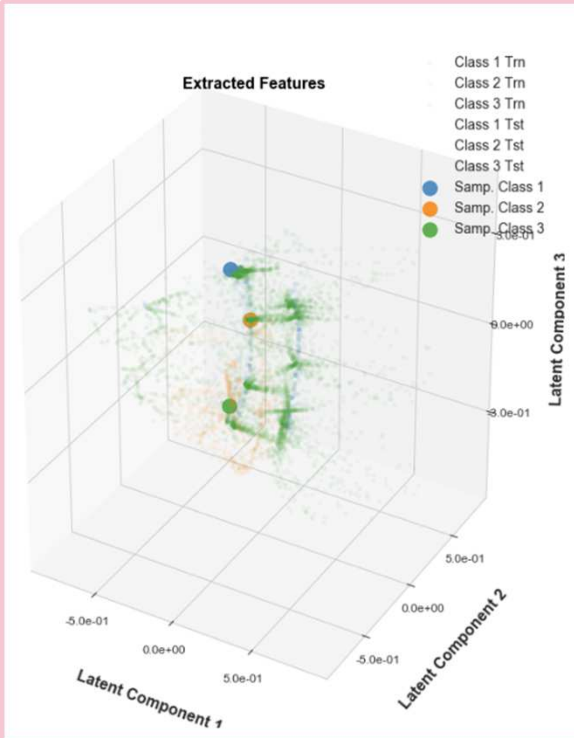
Classes



Input-Output Couples



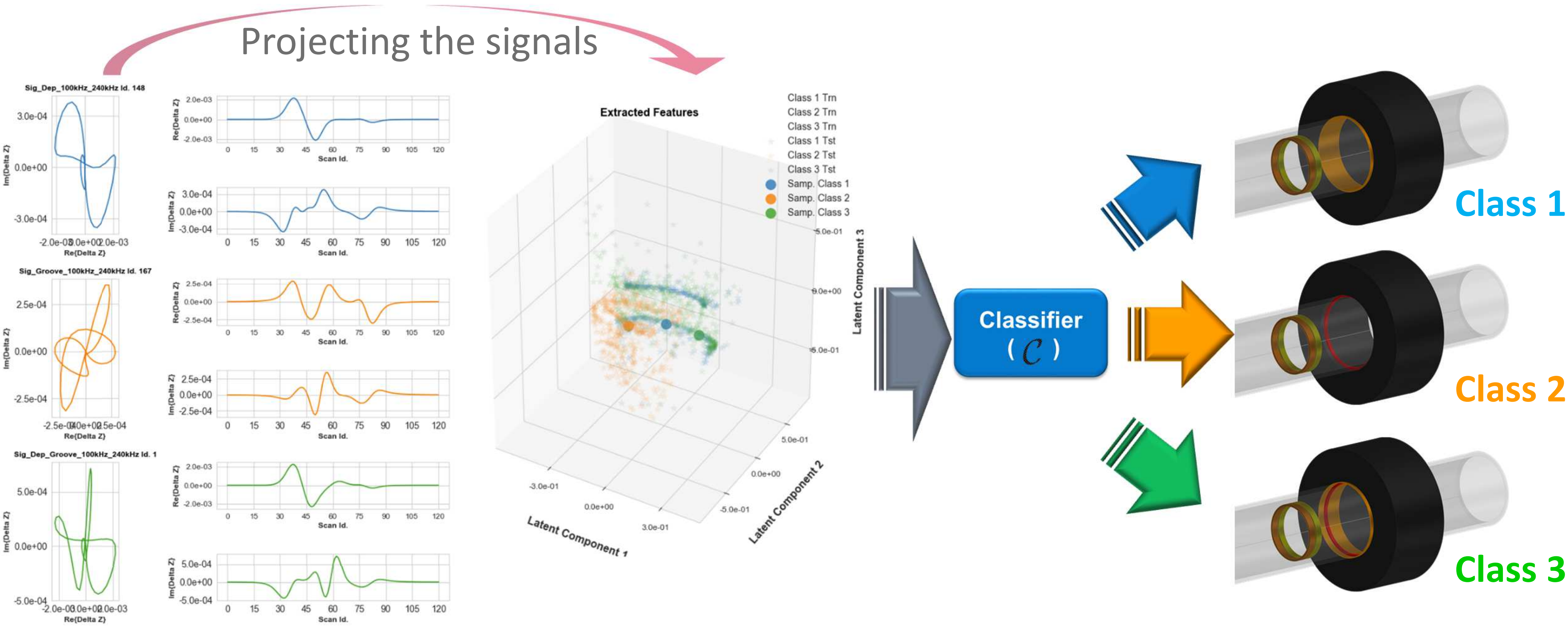
Extracted Features



Learning extracted features vs. classes

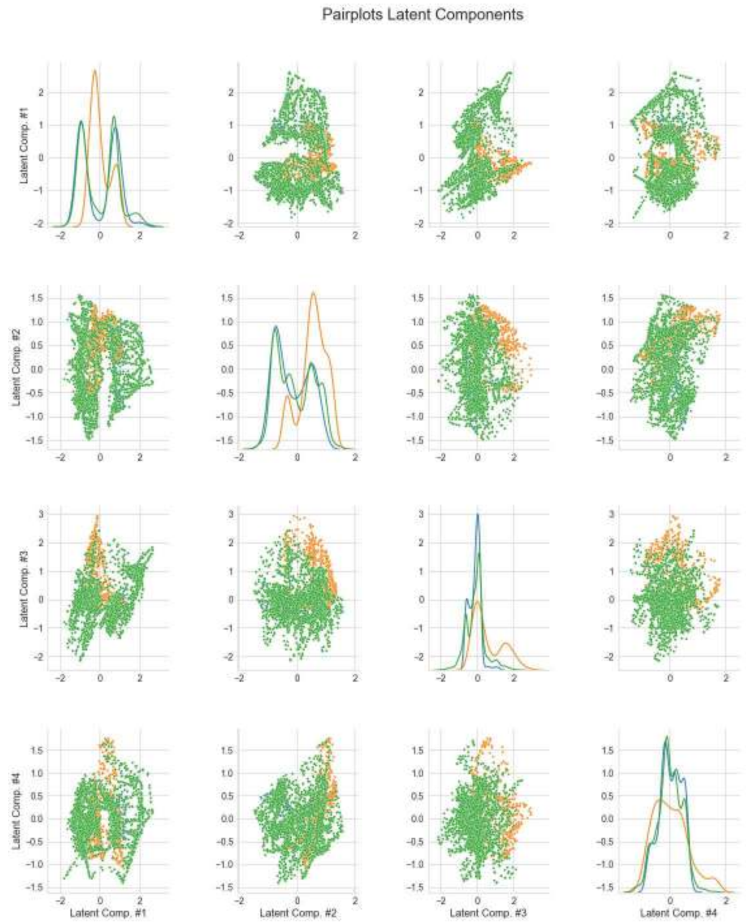
Classifier ($\mathcal{C}$)

Eddy Current Testing (ECT) classification tasks in steam generator tubes

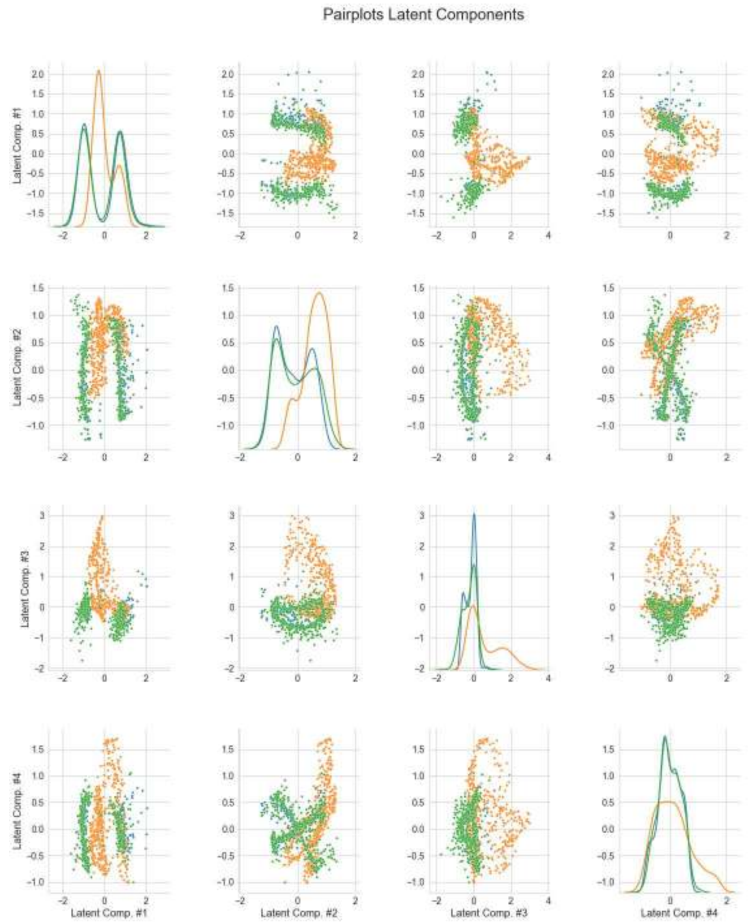


Eddy Current Testing (ECT) classification tasks in steam generator tubes

Pairplot of the first four PCA components associated to the training set



Pairplot of the first four PCA components associated to the test set



Dep
Groove
Dep_Groove

The two classes associated to "Deposit" and "Groove plus deposit" are well overlapped

→ **classification task not easy**

"Groove" class is well separated in the extracted feature space

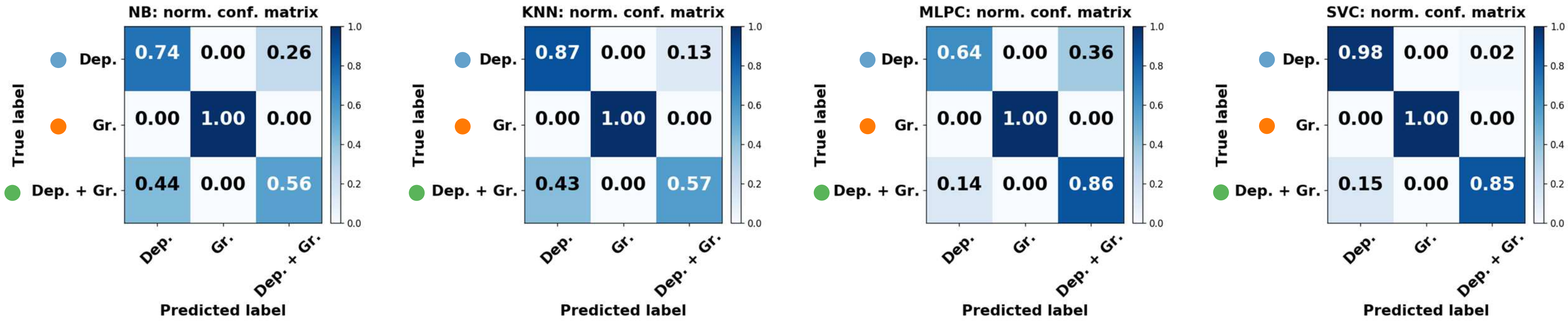
→ **classification possible with high accuracy**

Eddy Current Testing (ECT) classification tasks in steam generator tubes

Classification results

Accuracy

Naive Bayes → KNN → MLPC → SVC

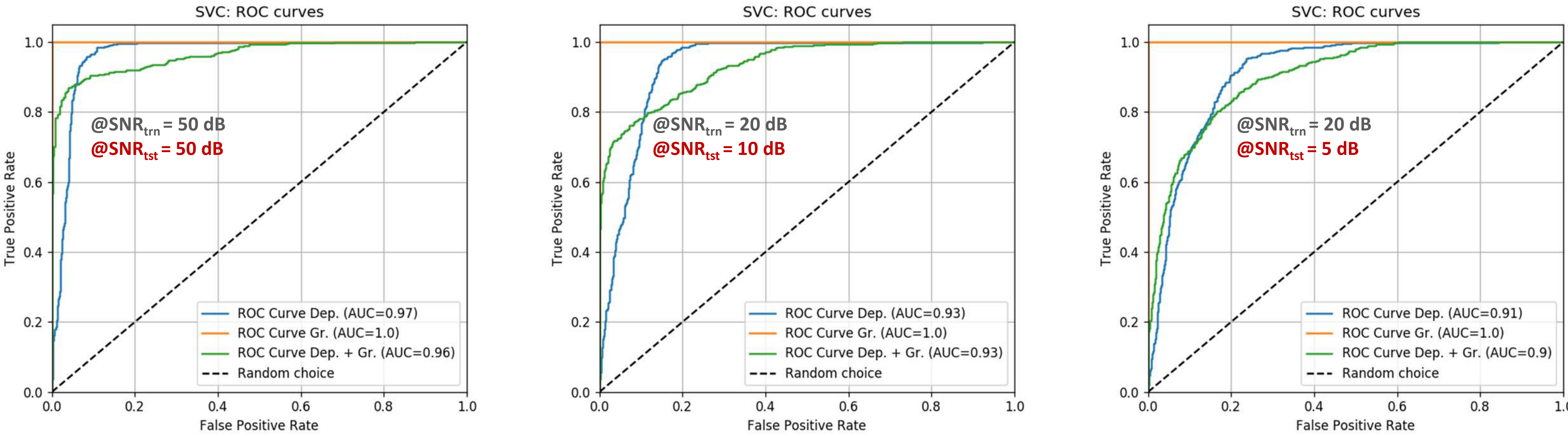


- Best results have been obtained with SVC
- Other classifiers struggle to discriminate “Deposit” vs. “Groove + Deposit”
- “Groove” signals are always well recognized
- Confusion matrices are adapted to compare classifiers providing discrete outputs (class nb.)

Eddy Current Testing (ECT) classification tasks in steam generator tubes

Classification results

Study of the robustness with respect to Additive White Noise (AWGN) corruption



- SVC classifiers is quite robust with respect to AWGN corruption up to SNR = 5 dB
- Major impacts on the classification accuracy are associated to the “Deposit” and “Deposit + Groove” classes

Structural Health Monitoring (SHM) inspection based on ultrasound guided wave imaging

- Structural Health Monitoring (SHM):

  "The process of acquiring and analyzing data from **on-board sensors** to evaluate the health of a structure"

  From: "Guidelines for Implementation of Structural Health Monitoring on Fixed Wing Aircraft", standard n°ARP6461, published by SAE International, 2013.

- Objectives:

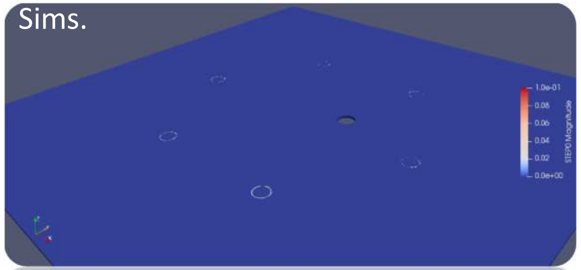
  The SHM system must certify the health of the structure until the next maintenance operation

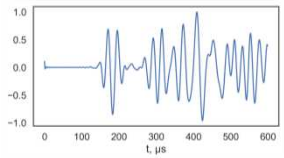
- Motivations:
  - **Simplification** of maintenance (accessibility)
  - **Condition-based maintenance** (remaining structural life estimation)
  - From scheduled maintenance towards SHM **triggered maintenance**
  - Better design by reduction of design security coefficients
  - **Structural life extension**

Structural Health Monitoring (SHM) inspection based on ultrasound guided wave imaging

Guided Wave Imaging (GWI): creation of an image providing a metric of the health of a specimen

GW- raw signals

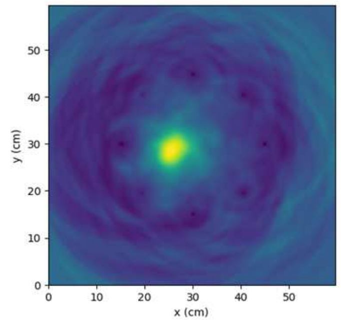




CIVA NDE

UT GWT

DAS GW imaging map

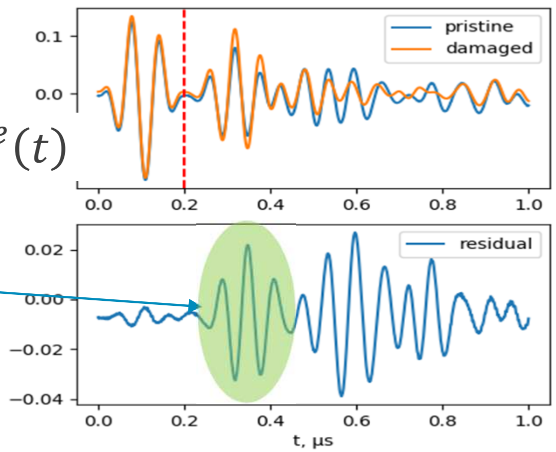


GWs residual signal

$$s_{i,j}(t) = S_{i,j}^{current}(t) - S_{i,j}^{baseline}(t)$$

GWs signals

Damage response



Delay-and-Sum[1] (DAS) algorithm:

1. Envelope of GWs residual signal:

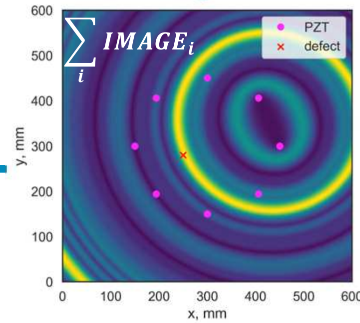
$$r_{i,j}(t) = \sqrt{s_{i,j}(t)^2 + i\hat{H}(s(t))^2}$$

2. GWs Time-Of-Flight (TOF):

$$TOF(x,y) = \frac{\sqrt{(x-x_i)^2 + (y-y_i)^2}}{C_g} + \frac{\sqrt{(x-x_j)^2 + (y-y_j)^2}}{C_g}$$

3. Compute Damage Index (DI)

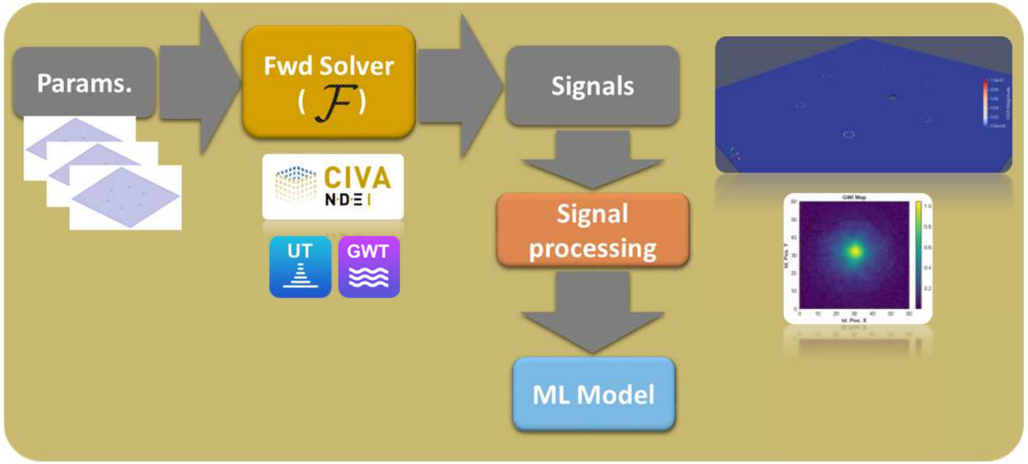
$$DI^{DAS}(x,y) = \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} r_{i,j}(TOF(x,y))$$



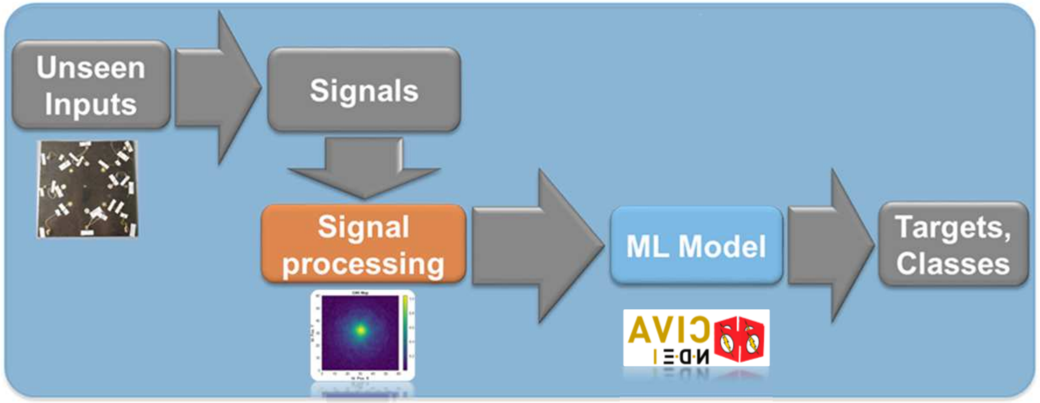
Structural Health Monitoring (SHM) inspection based on ultrasound guided wave imaging

Dataset and deep learning model generation

1. Off-line phase (possibly time consuming)



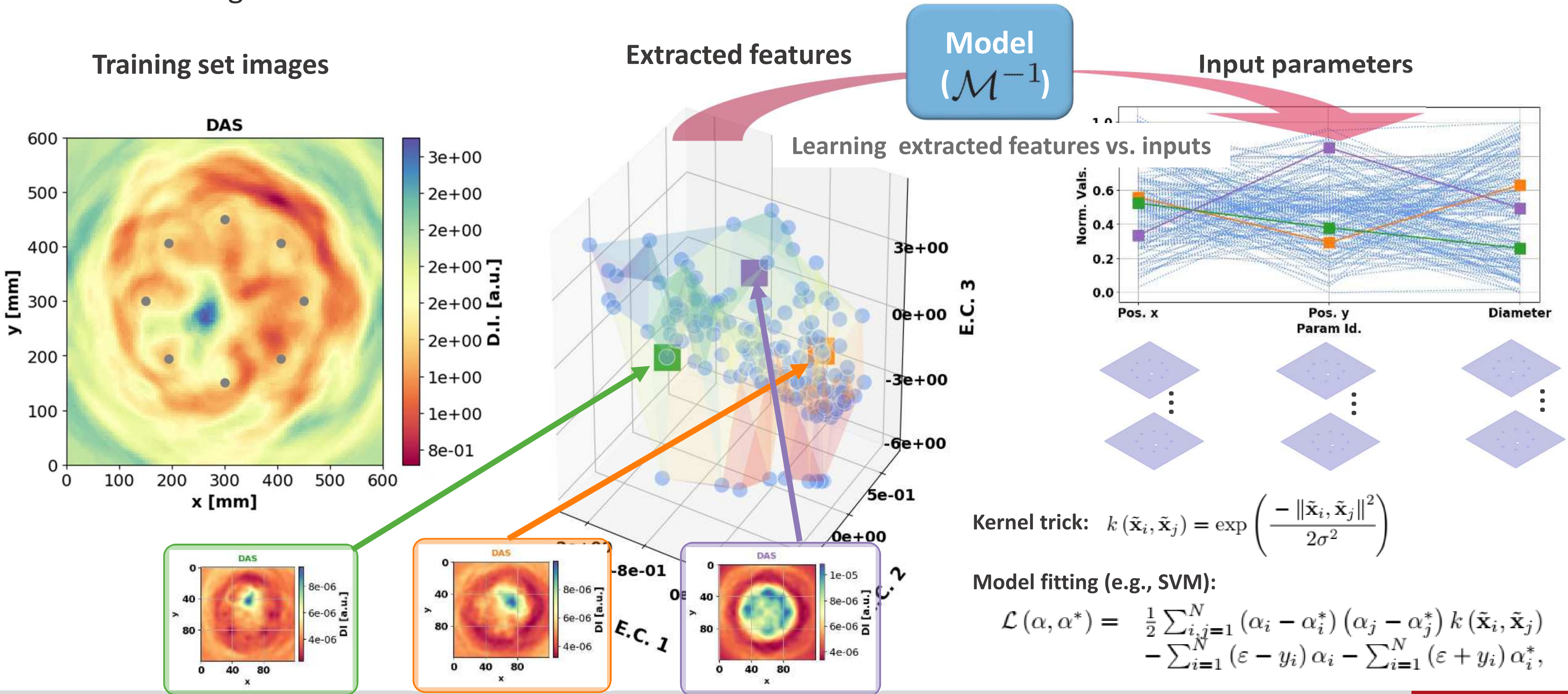
2. On-line phase (possibly almost real time)



- Machine learning model
  - Kernel-based regressor: Support Vector Regressor (SVR), kernel ridge regression, Gaussian process regression, etc.
  - Deep learning: multilayer perceptron, Convolutional Neural Network (CNN), recurrent neural network, etc.

Structural Health Monitoring (SHM) inspection based on ultrasound guided wave imaging

Kernel based regressor for flaw localization and characterization tasks



Kernel trick: $k\left(\tilde{\mathbf{x}}_i, \tilde{\mathbf{x}}_j\right) = \exp\left(\frac{-\|\tilde{\mathbf{x}}_i, \tilde{\mathbf{x}}_j\|^2}{2\sigma^2}\right)$

Model fitting (e.g., SVM):

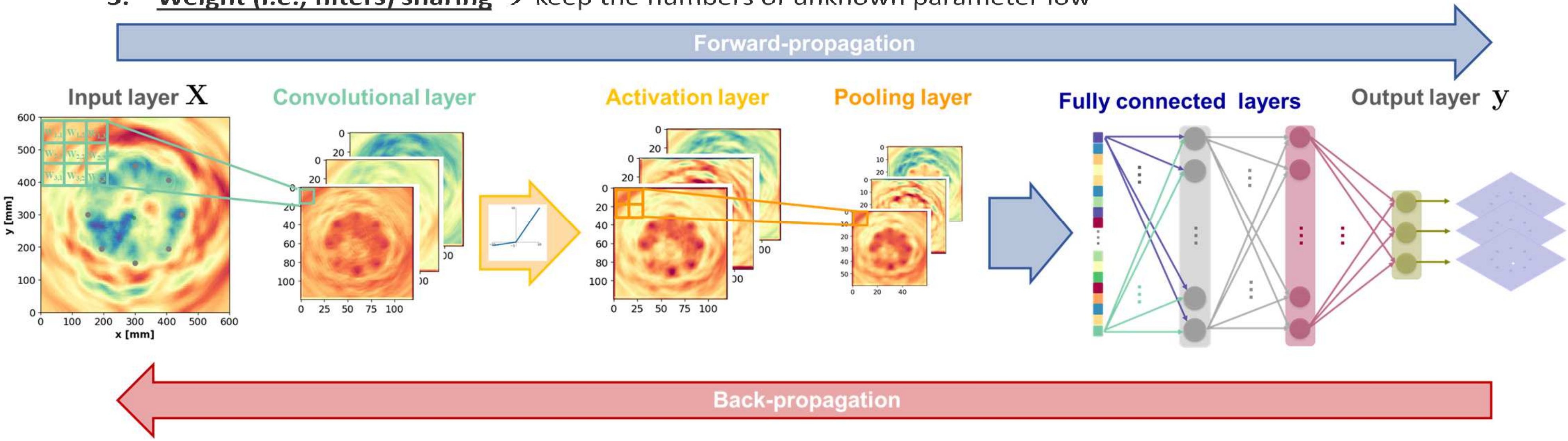
$$\mathcal{L}\left(\alpha, \alpha^*\right) = \frac{1}{2}\sum_{i,j=1}^{N}\left(\alpha_i - \alpha_i^*\right)\left(\alpha_j - \alpha_j^*\right) k\left(\tilde{\mathbf{x}}_i, \tilde{\mathbf{x}}_j\right) - \sum_{i=1}^{N}\left(\varepsilon - y_i\right)\alpha_i - \sum_{i=1}^{N}\left(\varepsilon + y_i\right)\alpha_i^*,$$

Structural Health Monitoring (SHM) inspection based on ultrasound guided wave imaging

Convolutional deep neural network architectures for flaw localization and characterization tasks

Convolutional Neural Network (CNN) [LeC1998] overcome MLP limitations thanks to:

1. **Sparse interactions** → convolutional kernel smaller than the inputs => higher computational efficiency
2. **Translation invariance** → shared patterns among layers
3. **Weight (i.e., filters) sharing** → keep the numbers of unknown parameter low



- The (one convolution) activation matrix at the *k*-th layer is given by

$$\mathbf{a}_{i,j}^{(k)} = g^{(k)}\left(\mathbf{z}_{i,j}^{(k)}\right)$$

$$\mathbf{z}_{i,j}^{(k)} = \boxed{\mathbf{W}_{A,B}^{(k-1)}}\mathbf{a}_{i,j}^{(k-1)}$$

Weights are the **same for a given feature map** and for all layers → the size is imposed by the kernel

Convolutional and pooling layers enable to train **fewer parameters** compared to a MLP

Structural Health Monitoring (SHM) inspection based on ultrasound guided wave imaging

Problem parameters

- 8 piezo-electric sensors
- Aluminum plate

Defect parameters

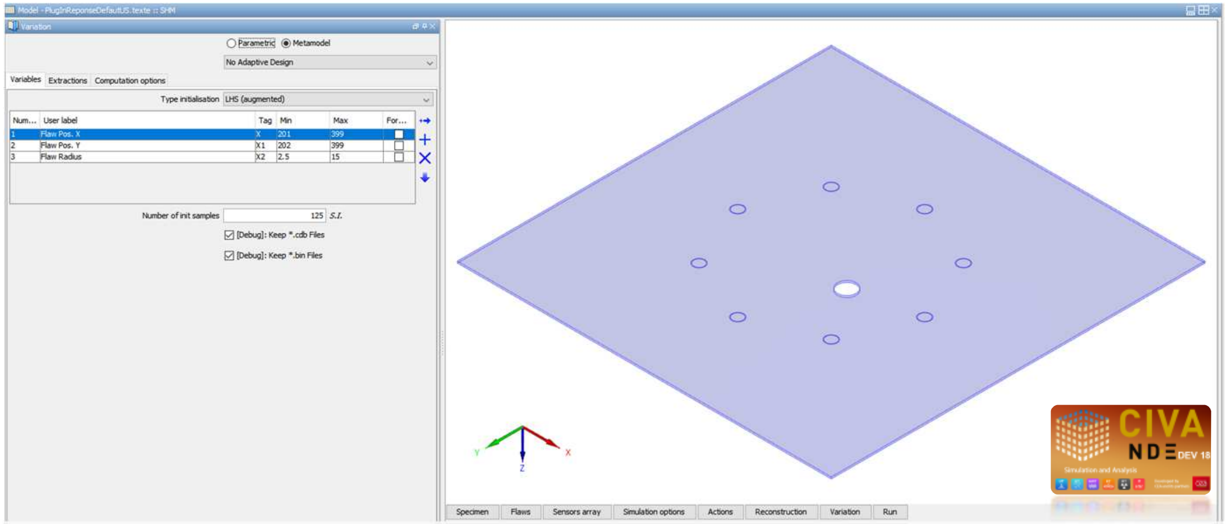
Default Params.	Var. Range
Pos. x [mm]	[200, 398]
Pos. y [mm]	[201, 399]
Defect radius [mm]	[2.5, 7.5]

Experimental defect parameters

Default Params.	Var. Range
Pos. x [mm]	[250]
Pos. y [mm]	[280]
Defect radius [mm]	[2.5, 3.0, 3.5, 4.0, 4.5, 5.0, 5.5, 6.0, 7.5]

Support vector machine with PCA

	PCA + SVR Params.
Cross-validation	5-folds
Num. features	9
SVR kernel	Gaussian
Error. Function	R2



Convolutional neural network setting

	CNN Params.
Num. epochs	1000 (with early stop)
Optimizer	Adam
Activation func.	ReLU
Num. Params	~30M
Architecture	2*CNN + Pool + CNN + Pool + 2*Dense

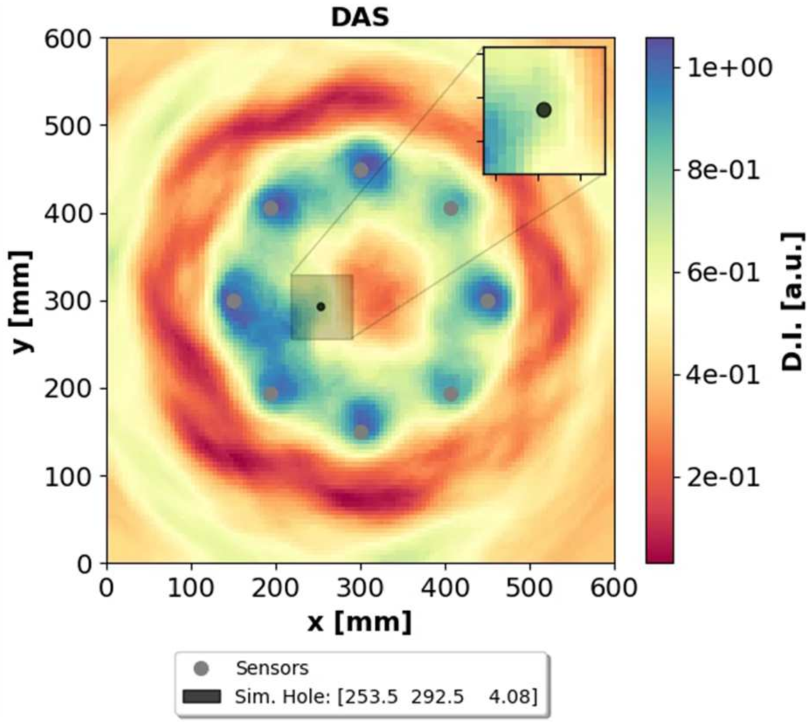
Structural Health Monitoring (SHM) inspection based on ultrasound guided wave imaging

Flaw(s) localization and size estimation in aluminum plate

Simulation budget considered (Latin hypercube sampling generated images)

Datasets	No. Samps.	Image size
Training	350/340	120 x 120
Validation	0/10	
Test	138 + 9 (Exp.)	

Examples of training set images



PCA + SVR

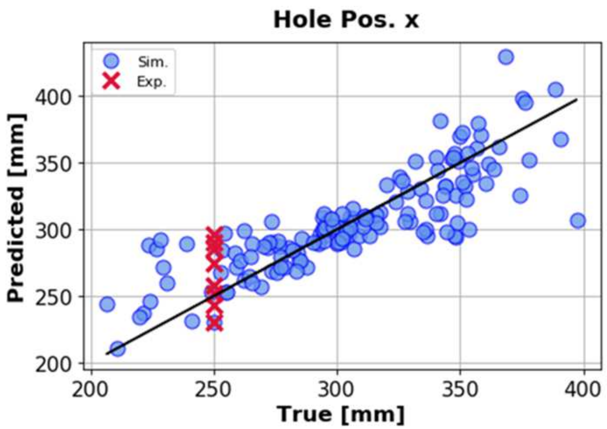
- **Training time ~60 min** on Dell Prescision 5520 with Intel Xeon E3-1505M v6 @3.0GHz and 32 GB RAM

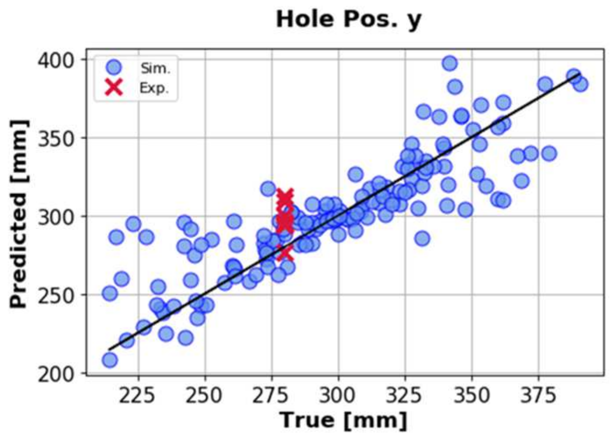
CNN

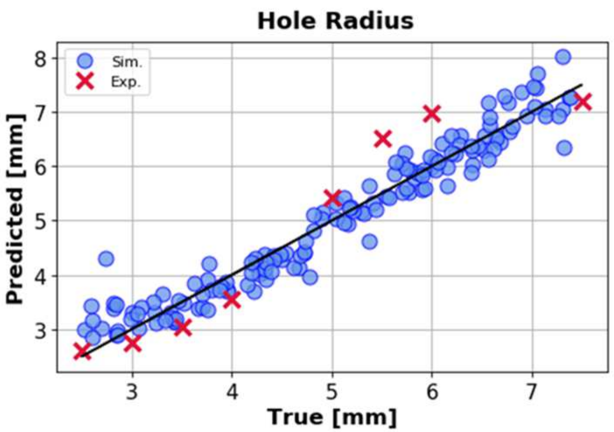
- Early stop @140 epochs
- Smooth learning curves obtained in the training process
- **Training time ~30 min** on Dell Prescision 5520 with Intel Xeon E3-1505M v6 @3.0GHz and 32 GB RAM

Structural Health Monitoring (SHM) inspection based on ultrasound guided wave imaging

Flaw(s) localization and size estimation in aluminum plate **PCA + SVR**



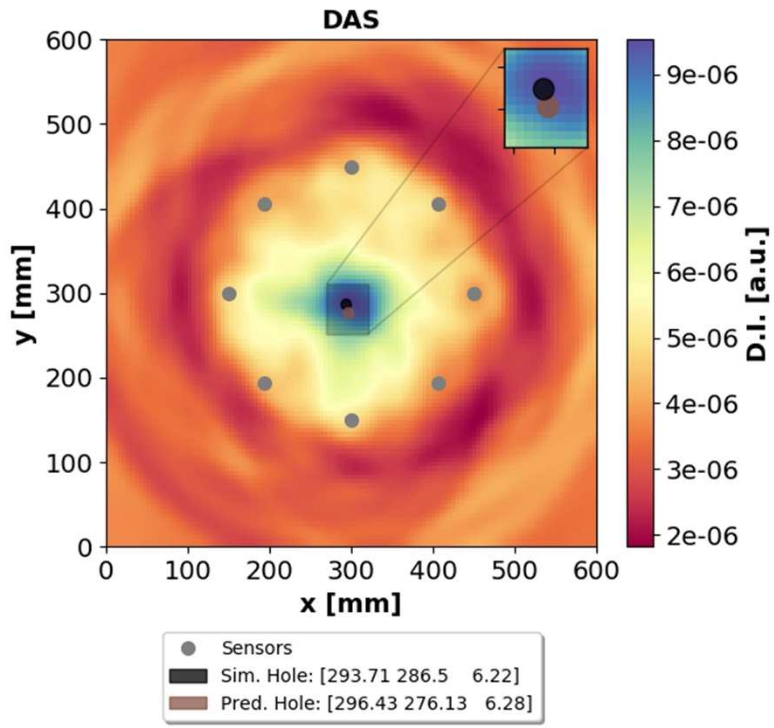




Errors	Pos. x	Pos. y	Radius
MAE	16.58	16.96	0.94
RMSE	23.33	22.39	0.36
R2	0.68	0.69	0.94

Predictions time ~0.025s on 138 + 9 test samples

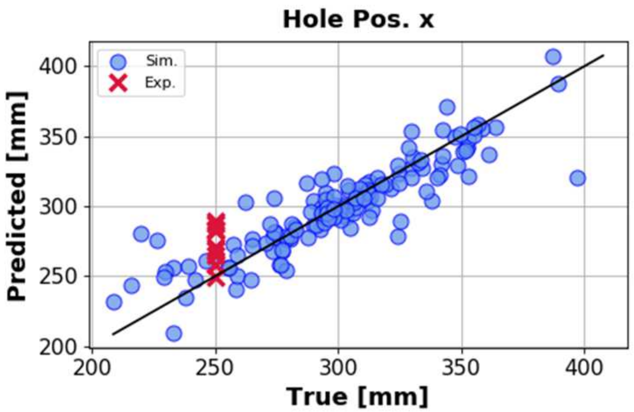
Predicted parameters

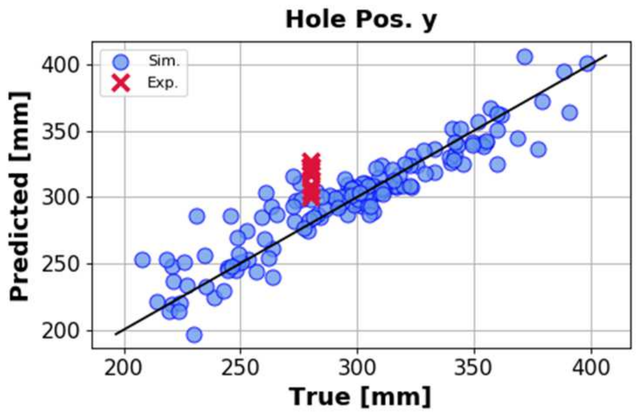


Error prone defect localization estimation and good defect radius characterization

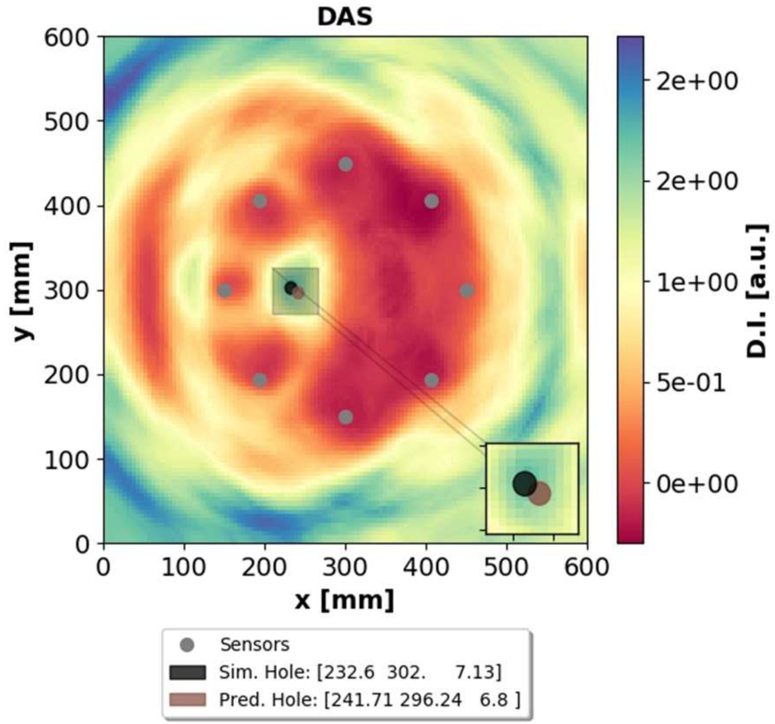
Structural Health Monitoring (SHM) inspection based on ultrasound guided wave imaging

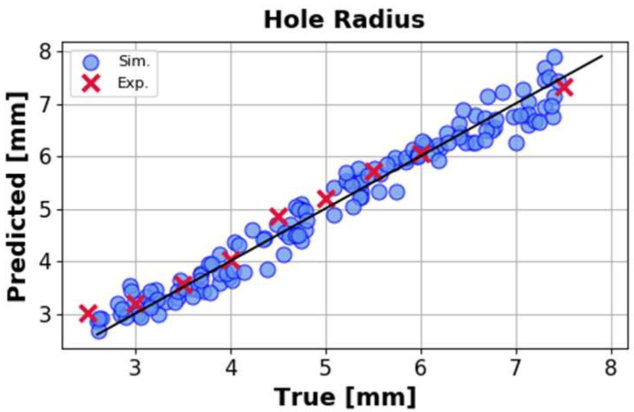
Flaw(s) localization and size estimation in aluminum plate with **CNN**





Predicted parameters





Errors	Pos. x	Pos. y	Radius
MAE	11.39	11.62	0.22
RMSE	16.67	15.98	0.27
R2	0.79	0.86	0.97

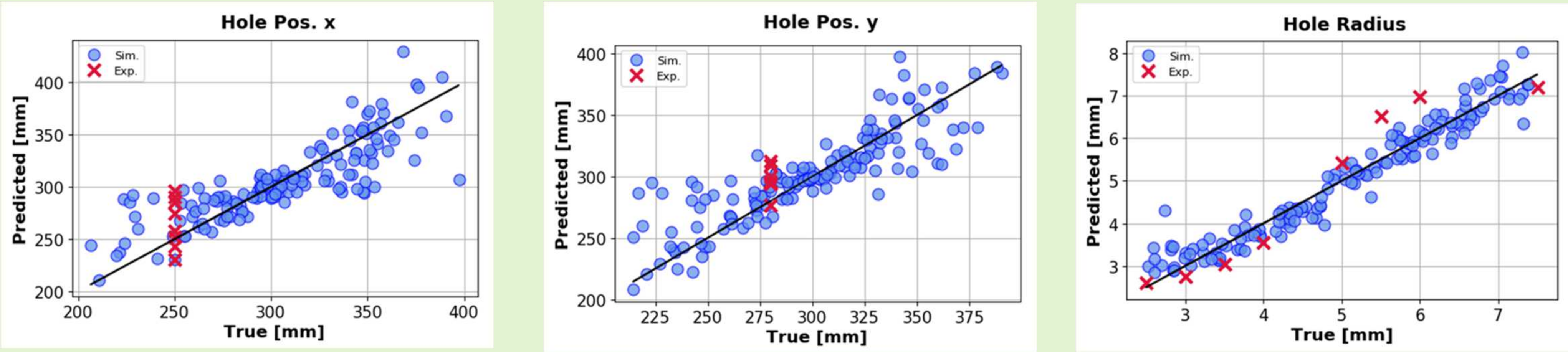
Predictions time ~1.6s on 138 + 9 test samples (on CPU)

Good defect localization estimation and radius characterization

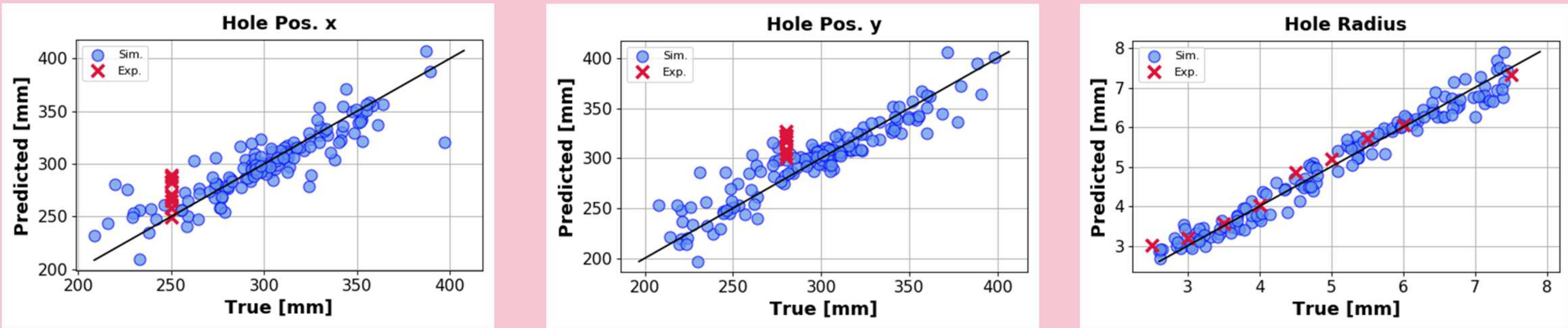
MODEL DRIVEN APPROACHES FOR NDT APPLICATIONS

Structural Health Monitoring (SHM) inspection based on ultrasound guided wave imaging

PCA + SVR



CNN



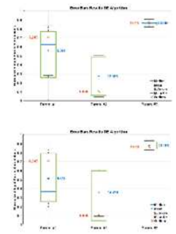
Part 3

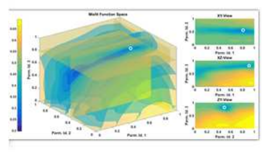
Wrapping up

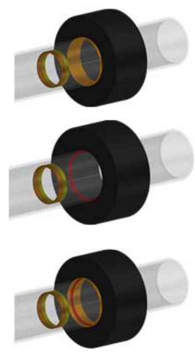
Conclusions (or the very beginning?)

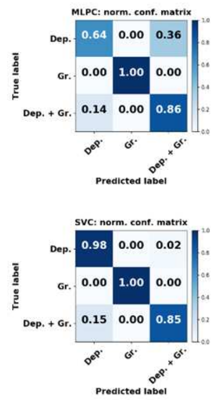
- Intensive use of simulations seems to be a viable way to address **fast inversion studies** applied to NdT problems (global stochastic inversion on noisy synthetic data (AWGN) **performs well** on UT signals)
- ML-based classification results in steam generator tube inspection provide **satisfactory outcomes** in challenging scenarios (ECT signal signature very similar)
- Evaluation of inversion performance of model-driven ML schemas with respect to **experimental situations** seems provide some **positive feedbacks** even though more experiments and test cases should be considered to better infer the inversion performance
- Similar performance is observed for other NdT problems addressed (e.g., UT inspections, pulsed-ECT)

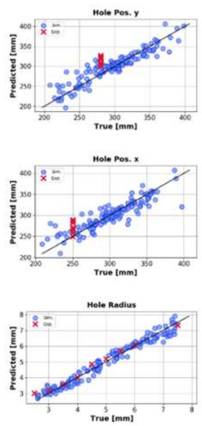
Is this sufficient to say that ML schemas to be straightforwardly deployed yet? (Un)fortunately not

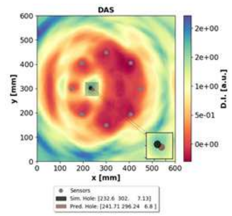












WRAPPING UP

Perspectives (or wishes?)

More NdT-physics into the deep neural network

Toward more advanced and problem-wise architectures

Physics-informed artificial neural network

More realistic NdT data

Measurement-driven approaches:

"Endless learning" methods → large experimental data will be collected in the near future (NdT companies are more and more aware of how much data precious are)

- Automatic labelling of NdT signals (ROI, label generation, indications, etc.)
- Incremental learning
- Transfer learning

Model driven approaches:

Generation of simulated data that "look like" the real experimental data

- Variational autoencoders (and variants)
- Generative adversarial networks (and variants)

- **Less "human control" on the DNN architecture**

AI driven approaches:

Automatic training and reinforced learning

Physics-Inspired Convolutional Neural Network for Solving Full-Wave Inverse Scattering Problems

Zhun Wei and Xudong Chen

Physics Informed Deep Learning (Part I): Data-driven Solutions of Nonlinear Partial Differential Equations

Maziar Raissi[1], Paris Perdikaris[2], and George Em Karniadakis[1]

[1]*Division of Applied Mathematics, Brown University, Providence, RI, 02912, USA*
[2]*Department of Mechanical Engineering and Applied Mechanics, University of Pennsylvania, Philadelphia, PA, 19104, USA*

Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks

Jun-Yan Zhu* Taesung Park* Phillip Isola Alexei A. Efros
Berkeley AI Research (BAIR) laboratory, UC Berkeley

AUTO-KERAS: EFFICIENT NEURAL ARCHITECTURE SEARCH WITH NETWORK MORPHISM

Haifeng Jin[1] Qingquan Song[1] Xia Hu[1]

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[…]

Thank You All!

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