International Conference on NDE 4.0
24 – 27 October 2022 in Berlin, Germany

Statistical analysis and automation through machine learning of resonant ultrasound spectroscopy data from tests performed on complex additively manufactured parts

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- Objectives
- Principle and advantages of RUS
- Description of the tested parts
- RUS examination of the tested parts
- Classification of the RUS data: Z-score analysis
- Clustering, classification and automation of RUS data: unsupervised and supervised machine learning (ML) analysis
- Summary and conclusions

Objectives

- **Objective 1**: Non-destructive volumetric quality inspection of a batch of **complex shape but also large/dense** additively manufactured (AM) parts supposedly identical:
  $\Rightarrow$ **Resonant Ultrasound Spectroscopy (RUS)**

- **Objective 2**: Statistical analysis and classification of RUS data of parts supposedly identical
  $\Rightarrow$ **Z-score** analysis

- **Objective 3**: Clustering, classification and automation of RUS data of parts supposedly identical to make the analysis operator independent
  $\Rightarrow$ **Supervised and unsupervised machine learning** (ML) analysis

Objectives

Principle and advantages of RUS

Description of the tested parts

RUS examination of the tested parts

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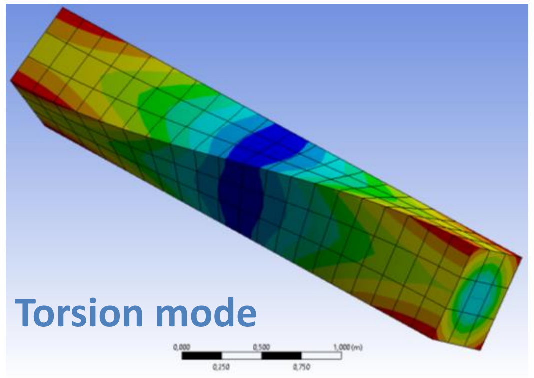
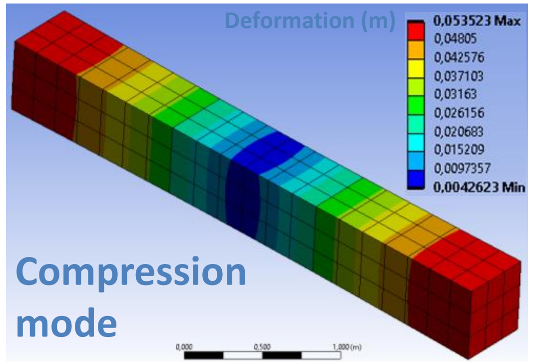
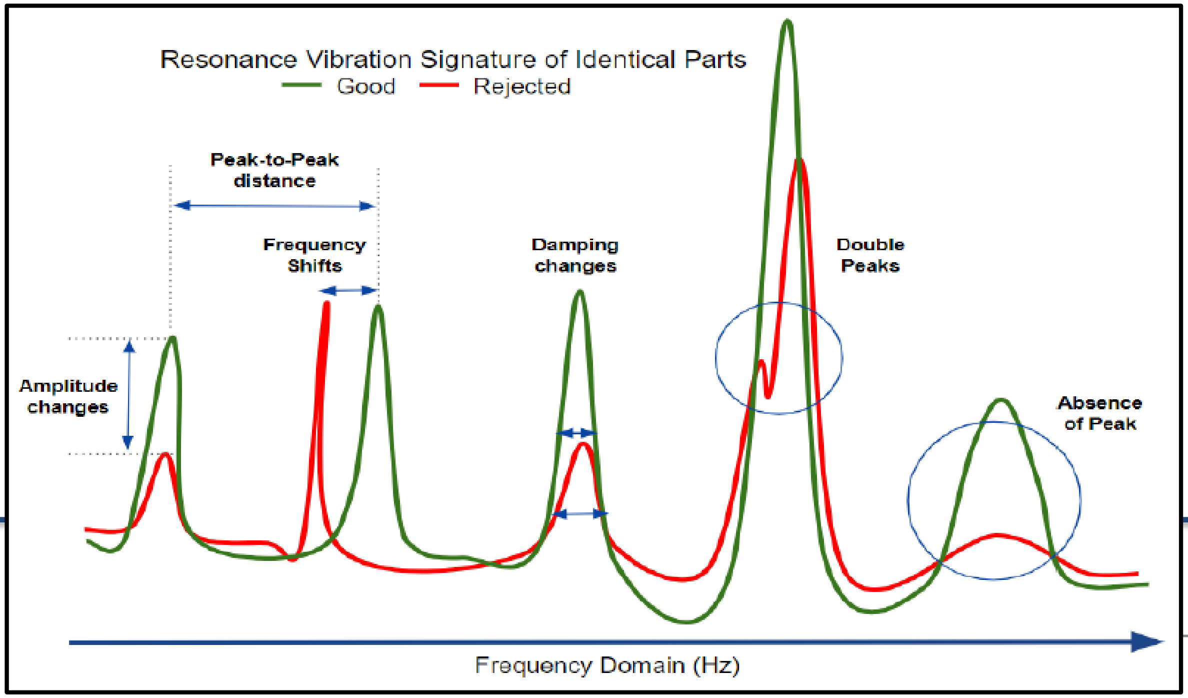
Summary and conclusions

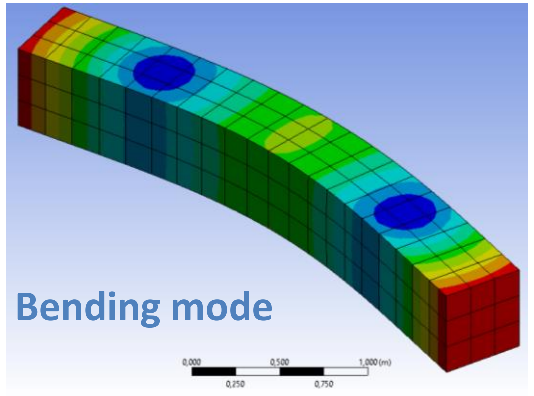
Principle and advantages of Resonant Ultrasound Spectroscopy (RUS)

Whole body non-destructive examination technique consisting in **exciting and recording**, in the acoustic and/or ultrasonic ranges, the **spectrum of the natural resonant frequencies of the vibration modes** of the part and then in **comparing** it **to the spectra of an established acceptable resonant frequency pattern** (reference parts or parts from the same group or simulations). Any **shift** in resonant frequency between the spectrum of the part under test and the spectra of the pattern will be the signature of a **difference** between the part and the pattern. Thus, the method enables classification of the parts as acceptable or unacceptable or according to their **intrinsic properties**.









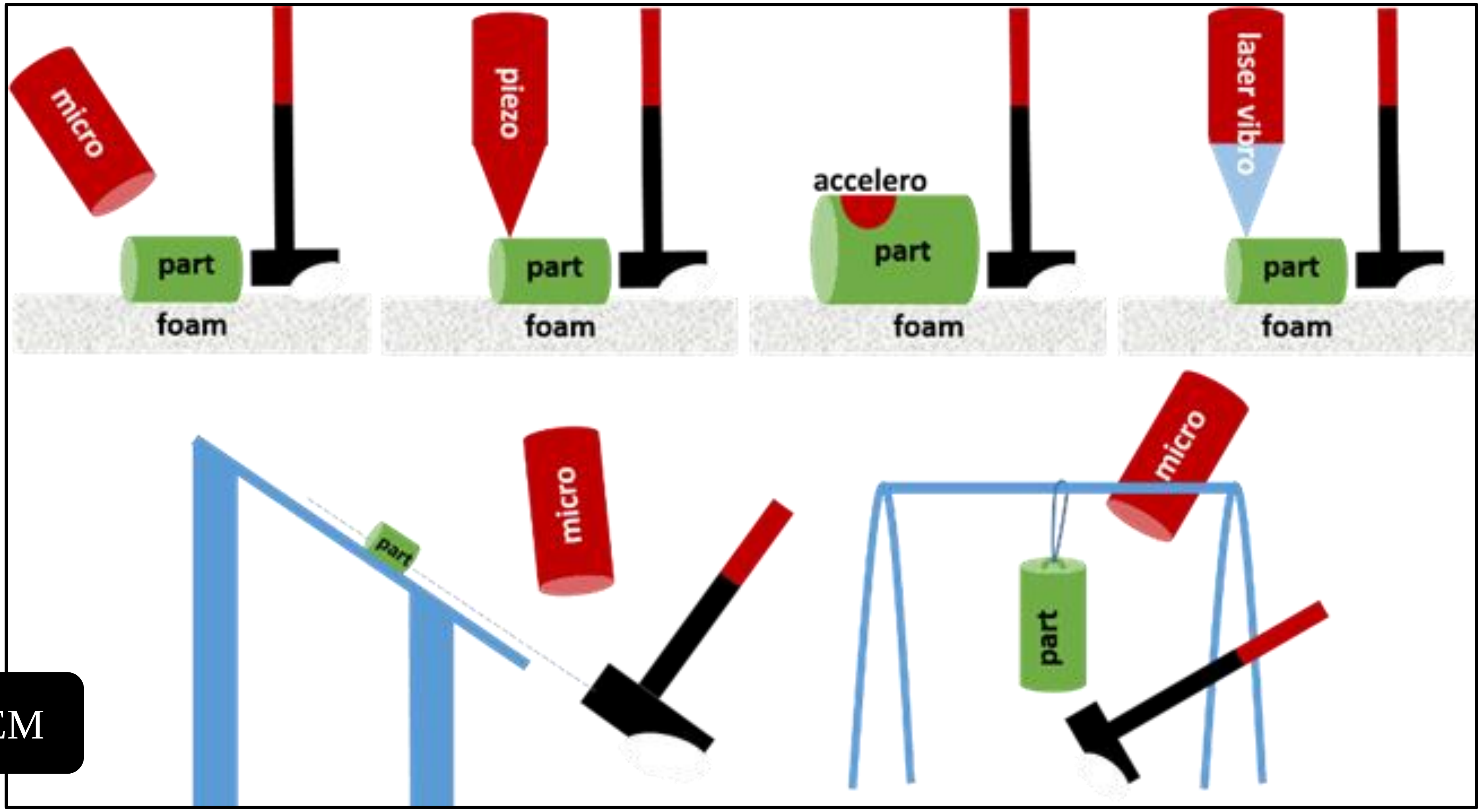
RUS takes on all the challenges that come with AM:

1. adapted to shape complexity,
2. adapted to high surface roughness,
3. adapted to any size/density,
4. easy to implement,
5. fast,
6. low cost.

Principle of Impulse Excitation Method (IEM), a RUS method

According to ASTM E2001 standard, RUS includes two types of methods:

1. swept sine
2. impulse excitation methods (IEM).



IEM

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Description of the tested parts

Laser beam Powder Bed Fusion: PBF-LB

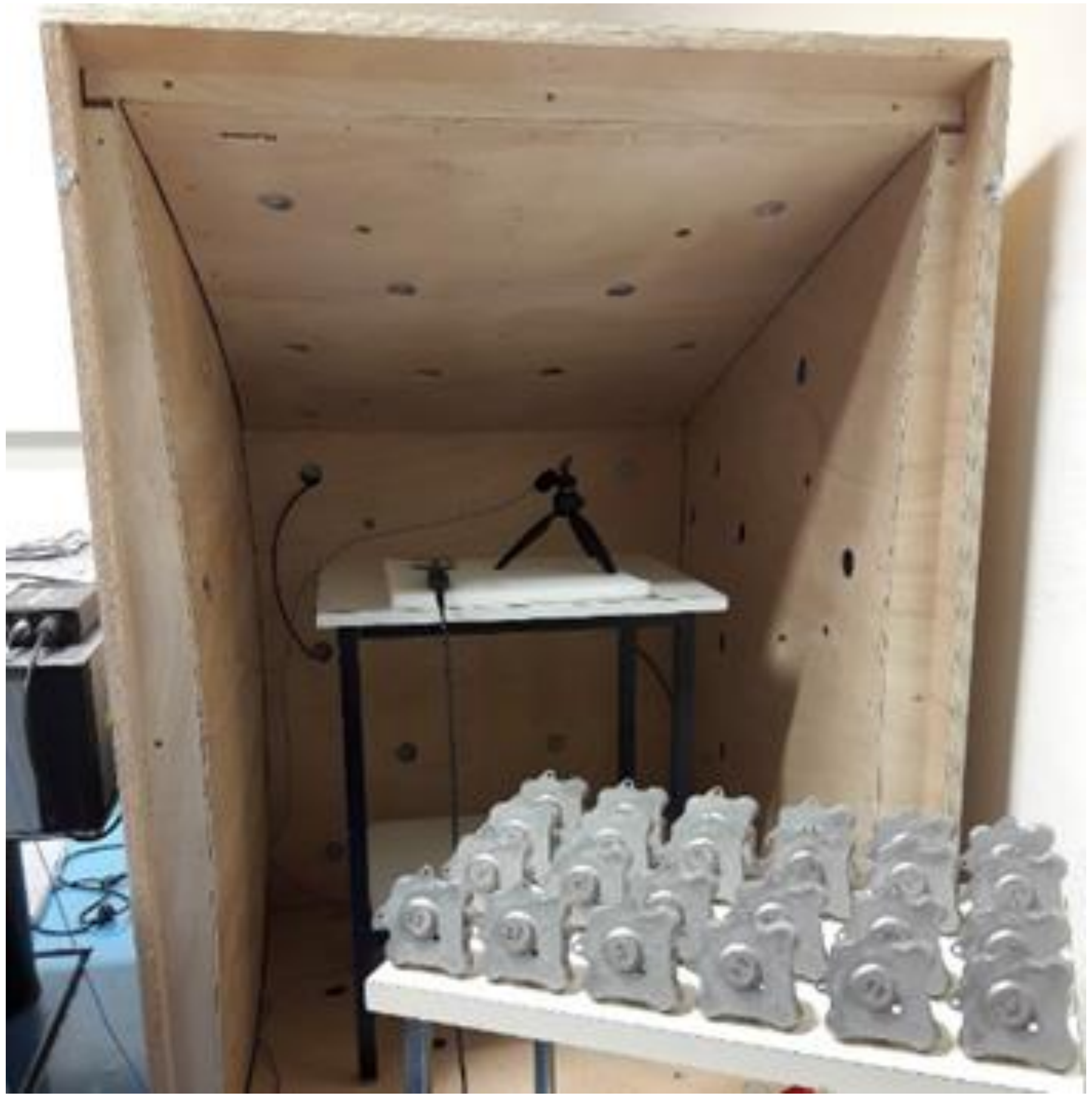
Batch of 24 additively manufactured parts, supposedly identical, in Ta6V, manufactured by Safran on 3 different platforms.

Objective 1

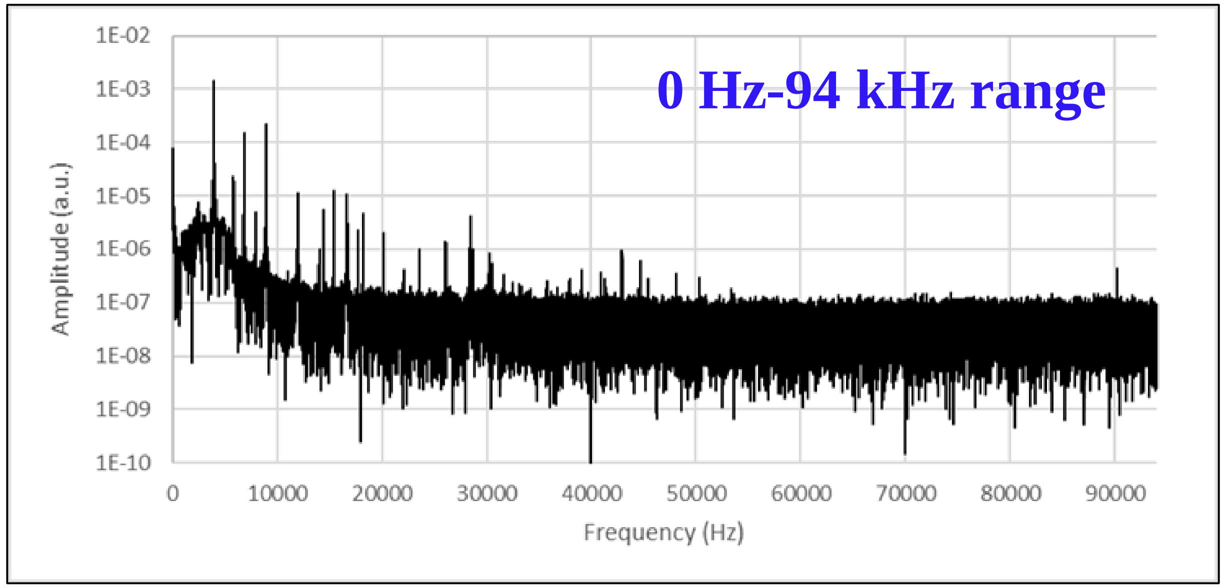
Objective 2

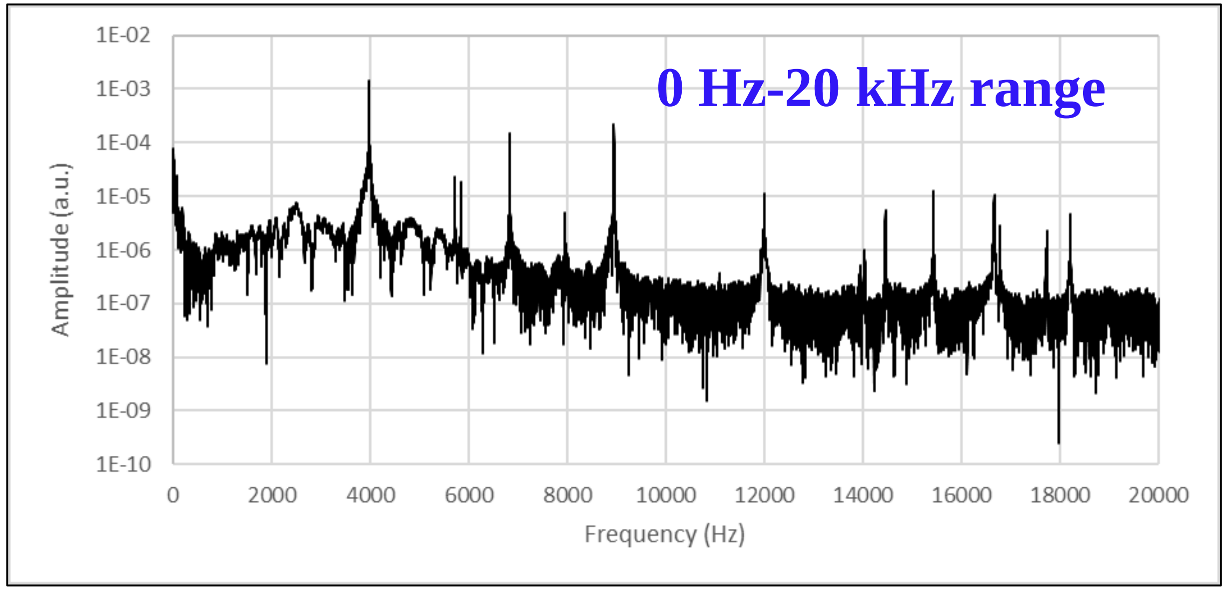
Objective 3

RUS (IEM) examination of the tested parts

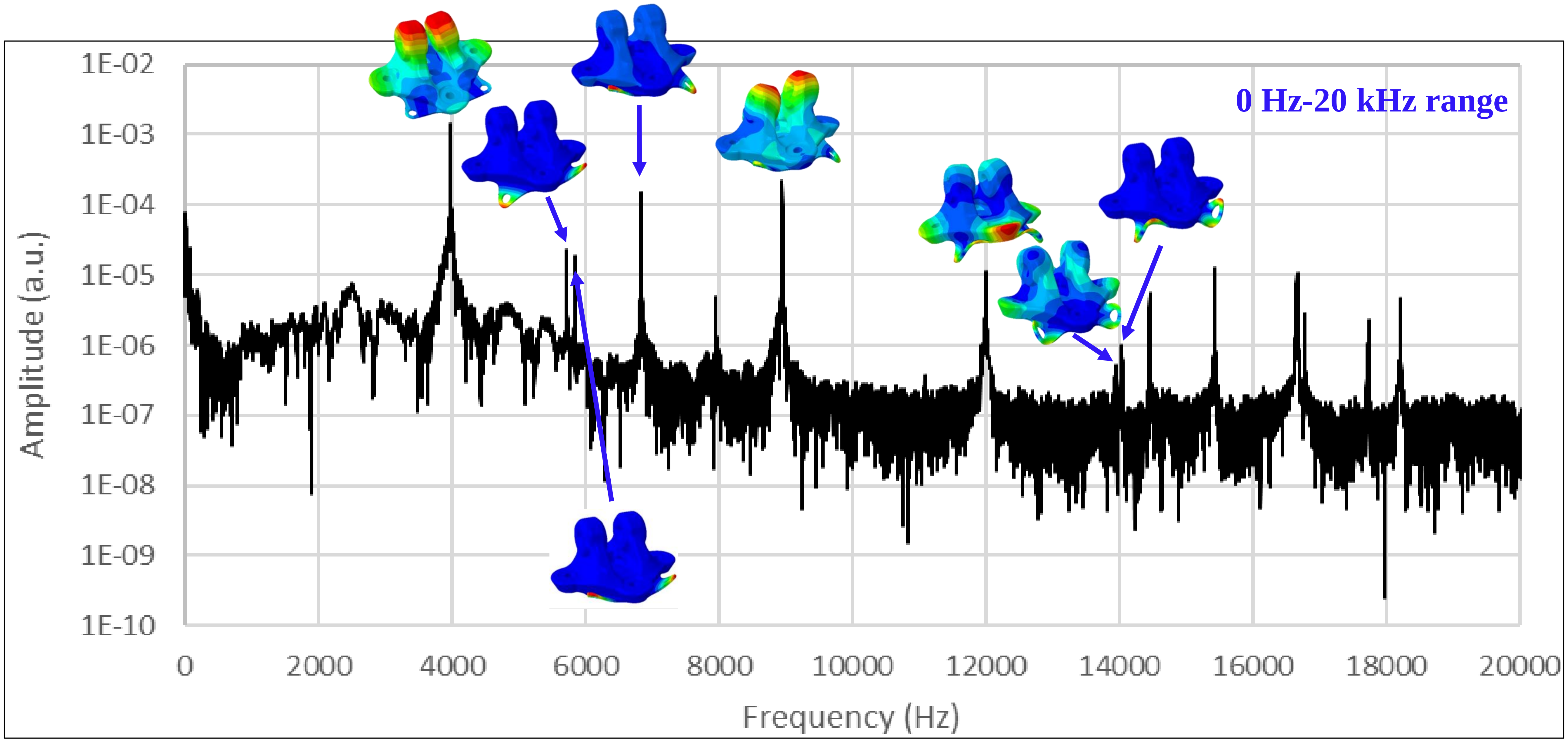


30 tests were performed on each parts





RUS (IEM) examination of the tested parts



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Statistical analysis and classification of the RUS data: Z-score analysis

Objective: classification of the parts, supposedly identical, into various risk categories computing Z-score statistical tool which offers a physical interpretation of the data.

Z-score:

- used to compare a sample's location within a population of reference samples,
- expresses the deviation of the sample from the mean value of the reference samples' population in term of standard deviation on the population taken as reference.

$$Z\ score = \frac{peak\ frequency\ of\ a\ sample - mean\ of\ the\ peak\ frequencies\ of\ a\ reference\ samples'\ population}{standard\ deviation\ of\ the\ peak\ frequencies\ of\ the\ reference\ samples'\ population}$$

Objective 1

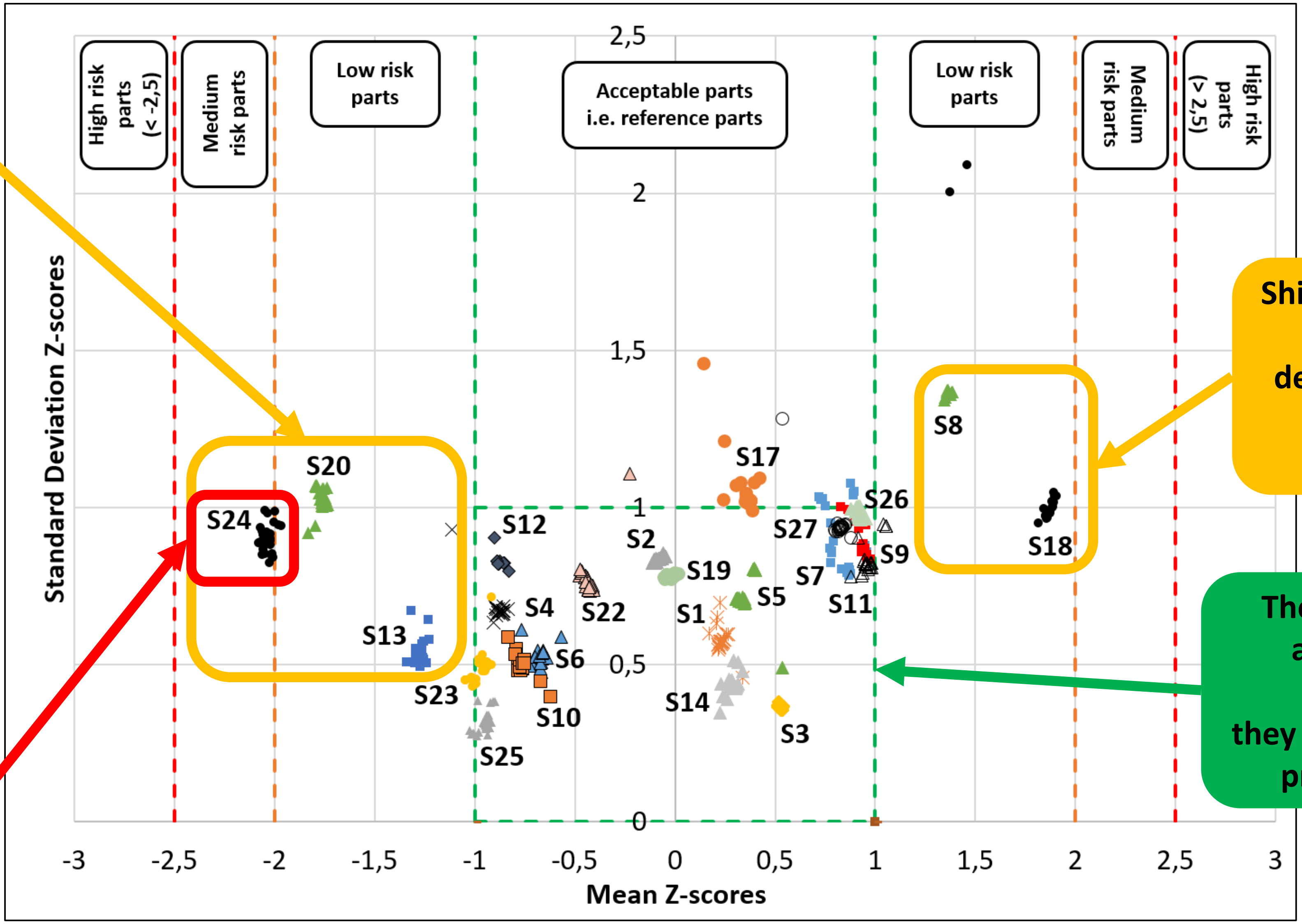
Objective 2

Objective 3

Statistical analysis and classification of the RUS data: Z-score analysis

Shift toward lower frequencies
⇒
deviation generally attributed to a defect or low mechanical properties

Higher shift toward lower frequencies
⇒
weakest part



Shift toward higher frequencies
⇒
deviation generally attributed to grain size, stress, or dimensional variations

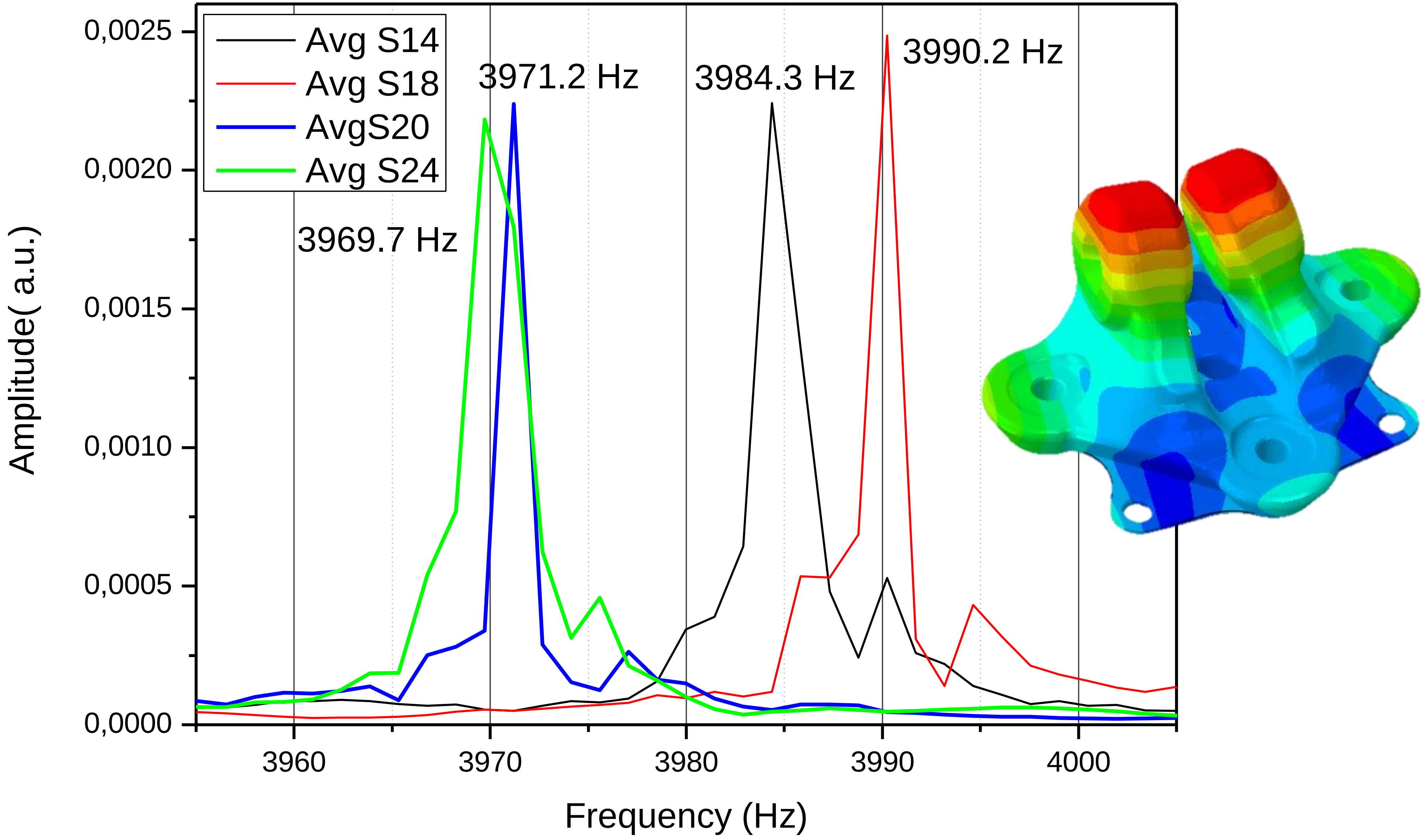
These parts respond similarly across all the frequencies
⇒
they should be similar in material properties and dimensions

Objective 1

Objective 2

Objective 3

Statistical analysis and classification of the RUS data: Z-score analysis



Objective 1

Objective 2

Objective 3

Clustering, classification and automation of RUS data: unsupervised and supervised machine learning (ML) analysis

Objective: Machine learning (ML), on the RUS data, was computed for the purpose of automating the whole analysis, to make the RUS analysis operator-independent.

1. Considering only the available RUS data, an unsupervised model was implemented. Then, based on the clustering performed by the unsupervised model, a supervised model was initiated.

2. Considering the available RUS data, as well as the results of the Z-score analysis to identify acceptable and unacceptable parts for labelling the data, virtual parts were generated. Then, several supervised models were implemented.

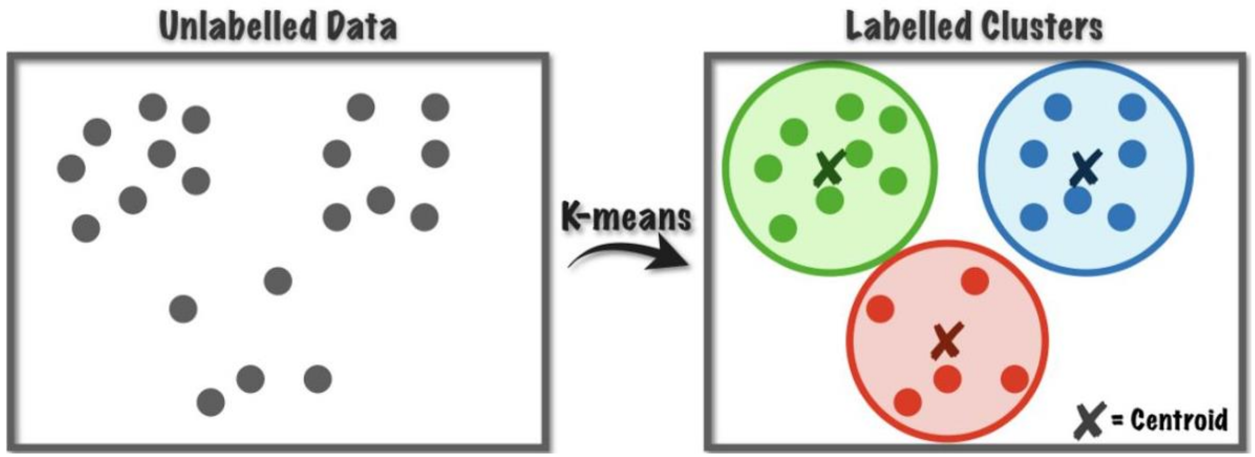
Objective 1

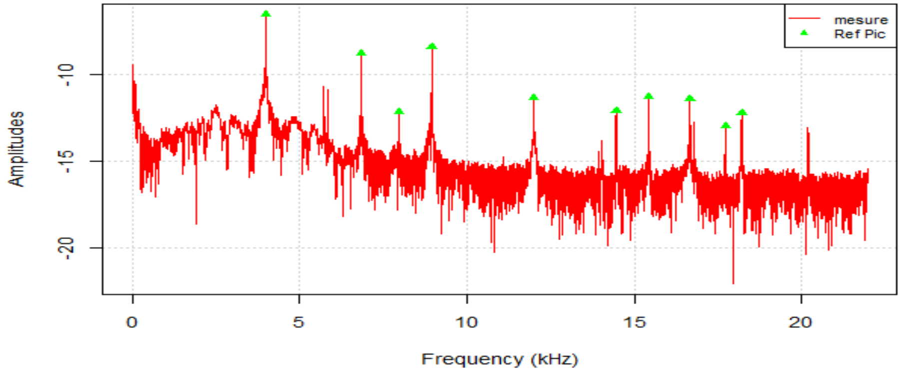
Objective 2

Objective 3

Unsupervised ML K-means model for data clustering

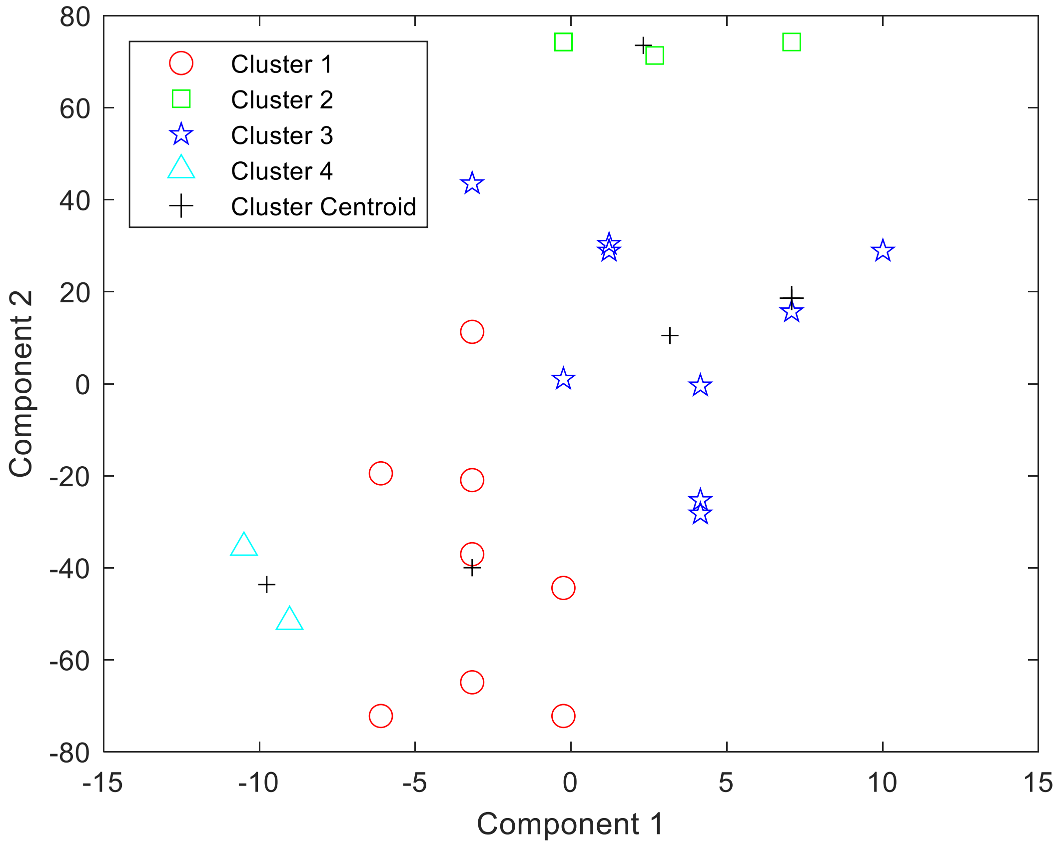
1. Considering only the available RUS data, an unsupervised model was implemented. Then, based on the clustering performed by the unsupervised model, a supervised model was initiated.





Frequencies (up to 20 kHz) at the maximum amplitude as input

Cluster number	Part number
Cluster 1	S2, S4, S6, S10, S12, S13, S23, S25
Cluster 2	S5, S8, S19, S27
Cluster 3	S1, S3, S7, S9, S11, S14, S17, S18, S22, S26
Cluster 4	S20, S24



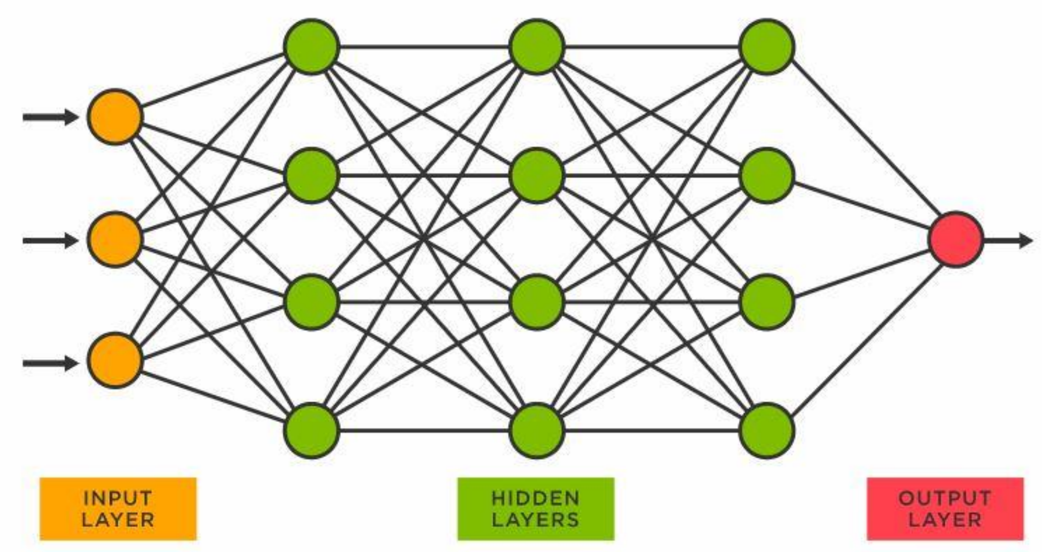
Objective 1

Objective 2

Objective 3

Supervised ML Neural Network (NN) model for linking the input and output data with a series of interconnected neurons

1. Considering only the available RUS data, an unsupervised model was implemented. Then, based on the clustering performed by the unsupervised model, a supervised model was initiated.



	Data splitting (%)	Mean squared error (MSE)	Coefficient of determination R
Training	70	0	1.0000
Validation	15	0.6180	0.9648
Test	15	0.0994	0.9307

R is close to 1 $\Rightarrow$ the fit and model are efficient $\Rightarrow$ K-means clustering method combined with NN supervised algorithm can be implemented as post-processing classification methods to automate the RUS data analysis.

Objective 1

Objective 2

Objective 3

Supervised ML analysis, based on labelled data with Z-score results, to classify parts

2. Considering the available RUS data, as well as the results of the Z-score analysis to identify acceptable and unacceptable parts for labelling the data, virtual parts were generated. Then, several supervised models were implemented.

To increase the amount of data, 9 virtual outliers and 68 inliers were generated (10 % outliers to be as representative as possible of industrial cases).

For better estimation of the capacity of prediction, a stratified cross-validation was performed: different train and validation sets were selected in a loop (70 % train and 15 % validation) and the capacity of prediction was computed at each iteration.
15 % of the data was kept for testing the model at the end of the cross-validation.

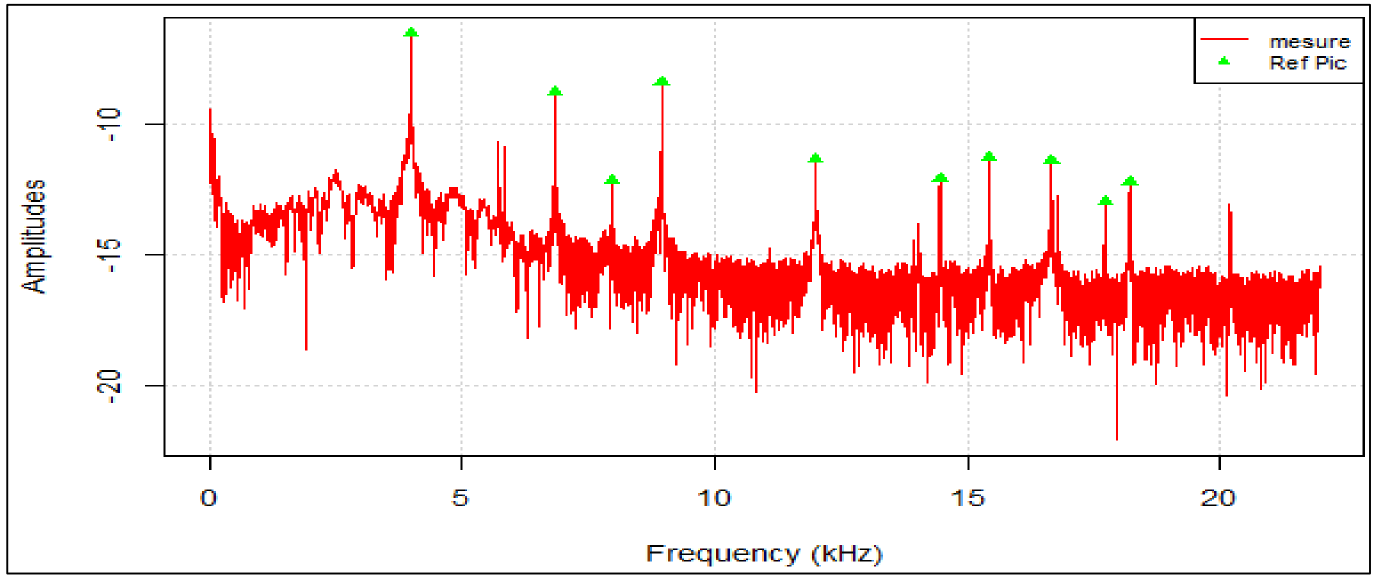
Objective 1

Objective 2

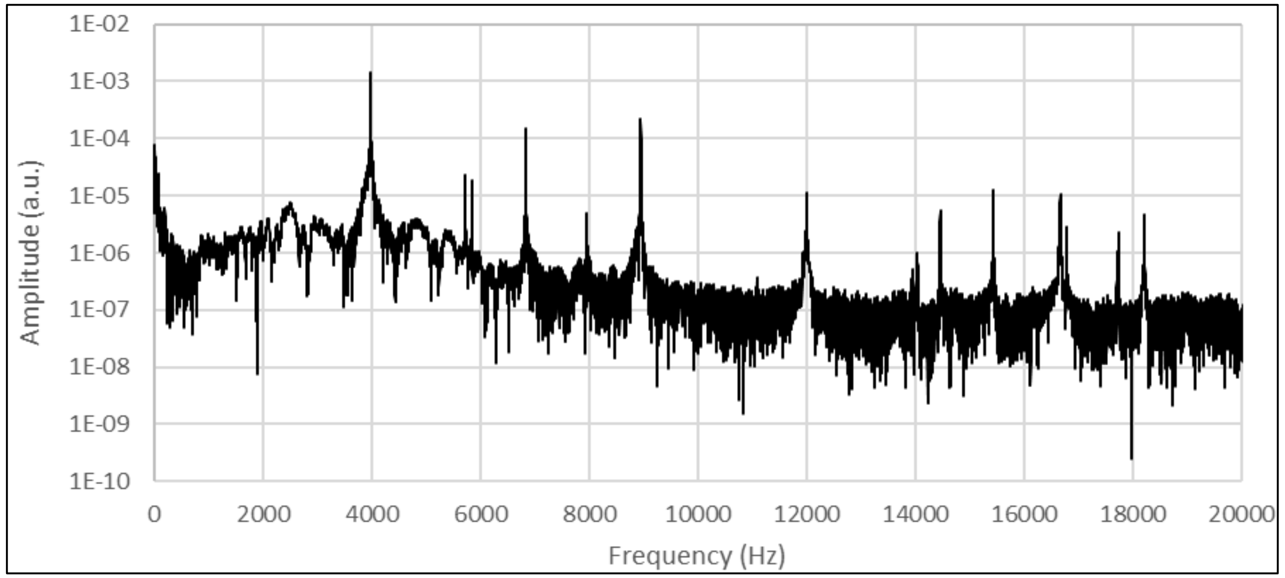
Objective 3

Supervised ML analysis, based on labelled data with Z-score results, to classify parts

Frequencies (up to 20 kHz) at the maximum amplitude as input



All spectrum (up to 20 kHz) as input + noise reduction



For the validation set

Model	mean accuracy	accuracy std	mean sensitivity	sensitivity std
SVM polynomial kernel	0.89	**0.04**	0.20	0.27
SVM radial kernel	**0.91**	0.06	0.30	0.44
Naïve Bayes	0.89	0.24	**1.00**	**0.00**

For the validation set

Model	mean accuracy	accuracy std	mean sensitivity	sensitivity std
SVM polynomial kernel	0.85	**0.03**	0.00	**0.00**
SVM radial kernel	0.88	0.10	0.30	0.45
Naïve Bayes	**0.92**	0.06	**0.53**	0.36

A good compromise between high accuracy and sensitivity is required ⇒ the Naïve Bayes model is the best model. It is more performing with frequencies at the maximum amplitude as input rather than with spectrum, also more time-consuming ⇒ the Naïve Bayes model was evaluated on the test set

Supervised ML analysis, based on labelled data with Z-score results, to classify parts

Evaluation of the Naïve Bayes model on the test set

Frequencies at the maximum amplitude as input

Prediction \ Target	1	0	Total
1	86.7% 13	0% 0	86.7% 13
0	0% 0	13.3% 2	13.3% 2
Total	86.7% 13	13.3% 2	15

All spectrum as input

Prediction \ Target	1	0	Total
1	86.7% 13	6.7% 1	93.3% 14
0	0% 0	6.7% 1	6.7% 1
Total	86.7% 13	13.3% 2	15

Confusion matrix

% true positive (acceptable parts predicted as acceptable)	% false negative (unacceptable parts predicted as acceptable)	Sum in row
% false positive (acceptable parts predicted as unacceptable)	% true negative (unacceptable parts predicted as unacceptable)	Sum in row
Sum in column	Sum in column	Number total of parts tested

One part was predicted false negative i.e. acceptable instead of unacceptable when using all spectrum as input which is not the case when using frequencies at the maximum amplitude as input. The model should be applied on frequencies at the maximum amplitude as input.

Supervised ML analysis, based on labelled data with Z-score results, to classify parts

To confirm that the Naïve Bayes model works properly, it was tested with the 24 real labelled parts with frequencies (up to 20 kHz) at the maximum amplitude as input

Prediction \ Target	1	0	Total
1	91.6% 22	0% 0	91.6% 22
0	4.1% 1	4.1% 1	8.2% 2
Total	95.7% 23	4.1% 1	24

One part over the 24 was not predicted correctly. It was predicted false positive i.e. unacceptable instead of acceptable. Otherwise, the rest of the parts was predicted correctly.

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Summary

- Application of Resonant Ultrasound Spectroscopy (RUS), through Impulse Excitation Method (IEM), on complex shape but also large/dense additively manufactured (AM) parts supposedly identical,
- Application of Z-score statistical analysis to classify RUS data of a batch of supposedly identical parts,
- Application of supervised models to automate the analysis of RUS data of a batch of parts with model trained on labelled parts.

Conclusions

- RUS is a performant volumetric NDT technique enabling to identify each part's conformity in regard to its group of like parts whatever their shape and surface roughness but also their size/density,
- RUS is easy to implement, fast and low cost,
- The inspection can be further accelerated if the RUS data analysis is performed with Z-score and/or supervised and unsupervised machine learning (ML) algorithms,
- Combined with ML analysis, the RUS data can be fully automated to make the analysis operator independent.

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Conclusions

Thanks for you attention

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