AIRCRAFT ENGINES

DETECTION OF ANOMALIES ON SIGNALS DURING AIRCRAFT ENGINE TESTS: METHODOLOGICAL COMPARISON BETWEEN HISTORICAL, STATISTICAL AND DEEP LEARNING APPROACHES

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EZAKO
Intelligence in Data

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CM2021
The future of condition monitoring
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This is now a virtual event

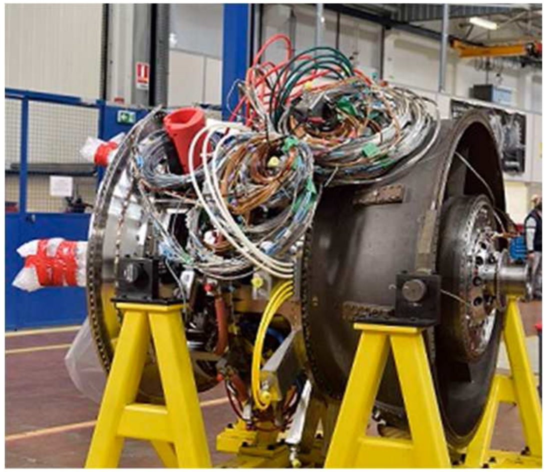
BINDT THE BRITISH INSTITUTE OF NON-DESTRUCTIVE TESTING

AGENDA

- Context
- Aim & Contributions
- Methodological comparison between different approaches
- Numerical experiments
- Conclusion

Context (1/2)

Engineering tests

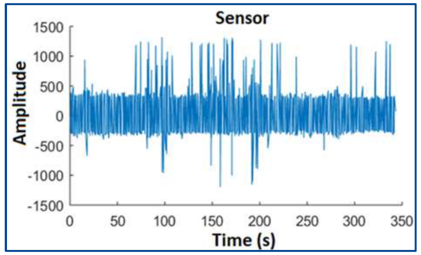


Tests on rotating parts

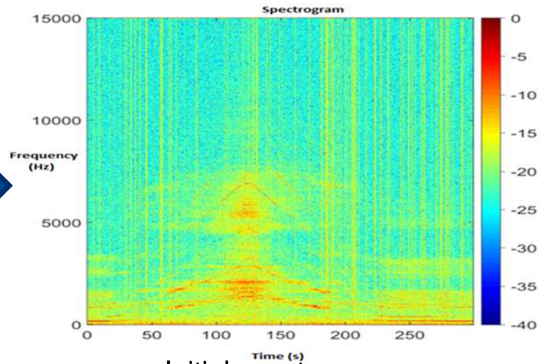
During tests on rotating parts, data is transmitted wirelessly to the acquisition computer.

Erroneous data can be transmitted from time to time.

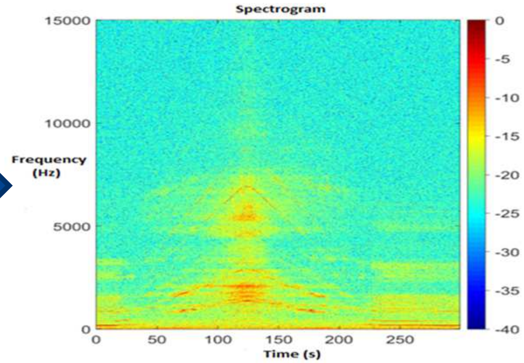
Context (2/2)



Received signal at computer bench



Initial spectrogram



Corrected spectrogram

The presence of abnormal observations in the signal can go as far as to make spectrograms completely unusable

The detection and correction of these abnormal observations becomes essential to continue to use the information contained in sensors.

Aim & Contributions

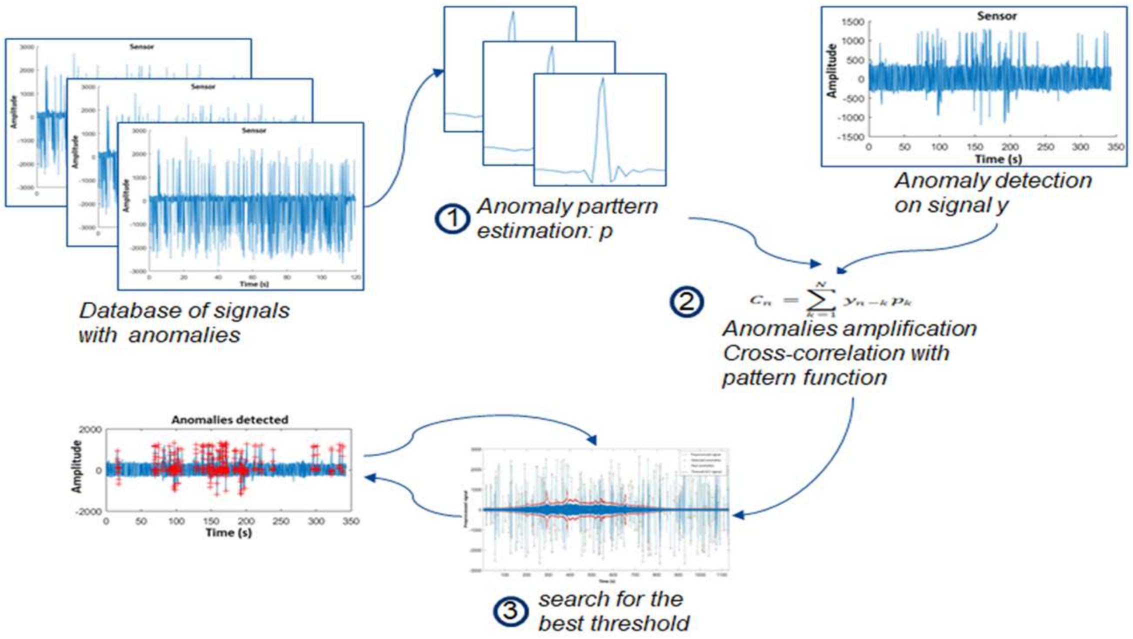
Focus of this work : Methodological comparison between three methods

- EBM, Expert-based methodology (historical approach)
- VSTD, a variant of the Rolling Standard Deviation method
- LSTM, Long Short Term Memory Autoencoder method

Contributions

- New methods detection performance similar to the one obtained via the expert-based method;
- Proposition of an LSTM auto-encoder architecture and variant of the well-known Rolling Standard Deviation developed by EZAKO;
- We prove that the new techniques are less burdensome in terms of computational time

EBM, Expert-based methodology (1/3)



Expert-based methodology performed according to 3 steps.

EBM, Expert-based methodology (2/3)

Anomaly pattern estimation

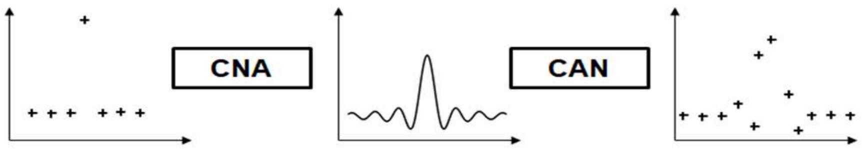
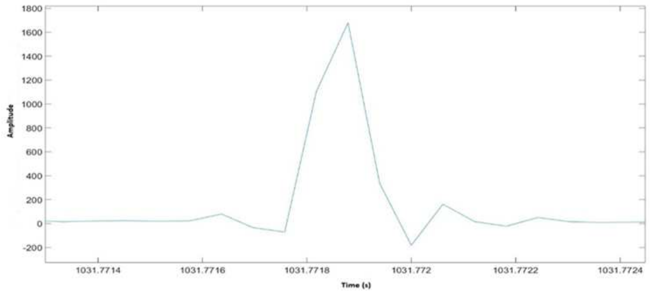


Diagram of the acquisition chain and its impulse response, after transmission



Anomaly pattern – cardinal sine

$$P(n) = 1_{[N_{min},N_{max}]}(n - n_0)\, sinc\left(p_f(n - n_0)\right)$$

$$sinc(x) = \frac{sin(\pi x)}{\pi x}$$

p_f : the pseudo-frequency of the cardinal sine

n_0 : the sample on which the anomaly is maximum

N_{min}, N_{max} : estimated to be -5 and 5

The presence of a numeric to analogic convertor (CNA) after transmission leads to have a cardinal sinus shape.

EBM, Expert-based methodology (3/3)

Anomaly amplification and detection

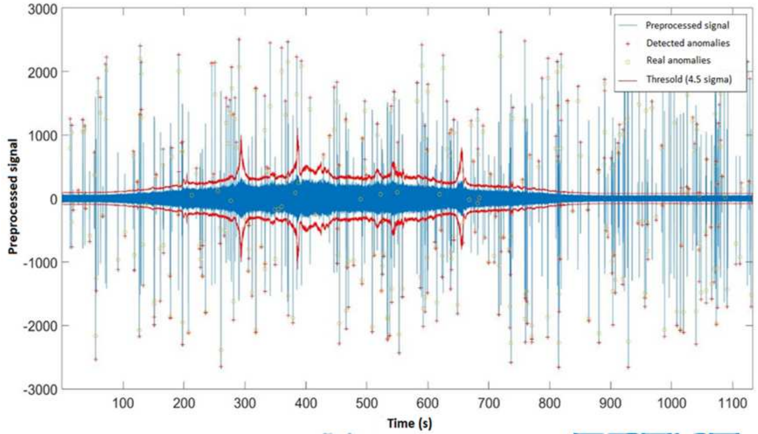
Anomalies made more visible in the signal by calculating cross-correlation between signal and centered anomaly pattern

$$C(x) = \int f(t-x)p_c(t)dt$$

Decision criteria : estimation of local mean and standard deviation

$$|y(k) - \widehat{m}(L,k)| > \alpha\hat{\sigma}(L,K)$$

The alpha parameter is set by the user, and may take several iterations, before making sure to detect the correct number of anomalies



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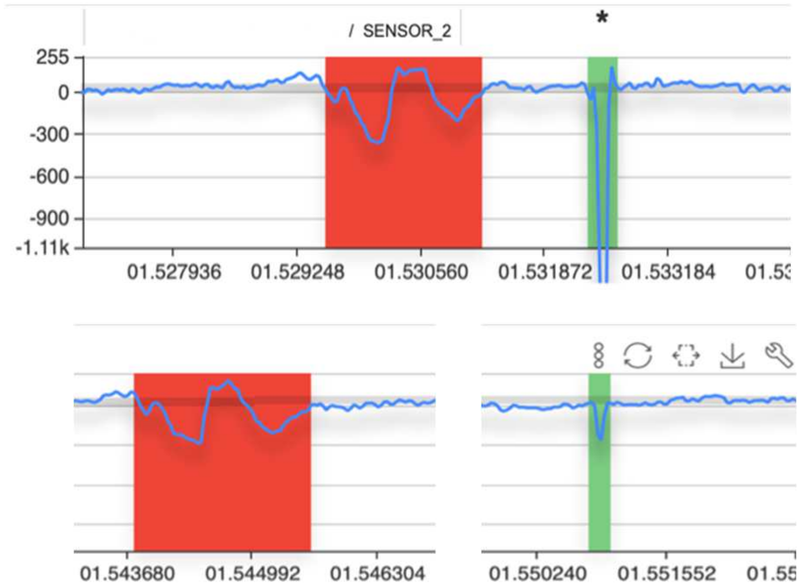
VSTD

A variant of the Rolling standard deviation method

- **This algorithm matches well the pattern we are looking for: data points are more dispersed than the nominal data**
  - ➢ When data point are more dispersed than the nominal data. Really sensitive to spikes. Less sensitive to a square wave.



- **Very fast**
- **No overfitting**
- **Adaptable on multiple sensor**
  - ➢ Rely on the dispersion of the local context. This is really suited when the signal has different behaviour.
- **parametric (σ: sigma, w: window size)**

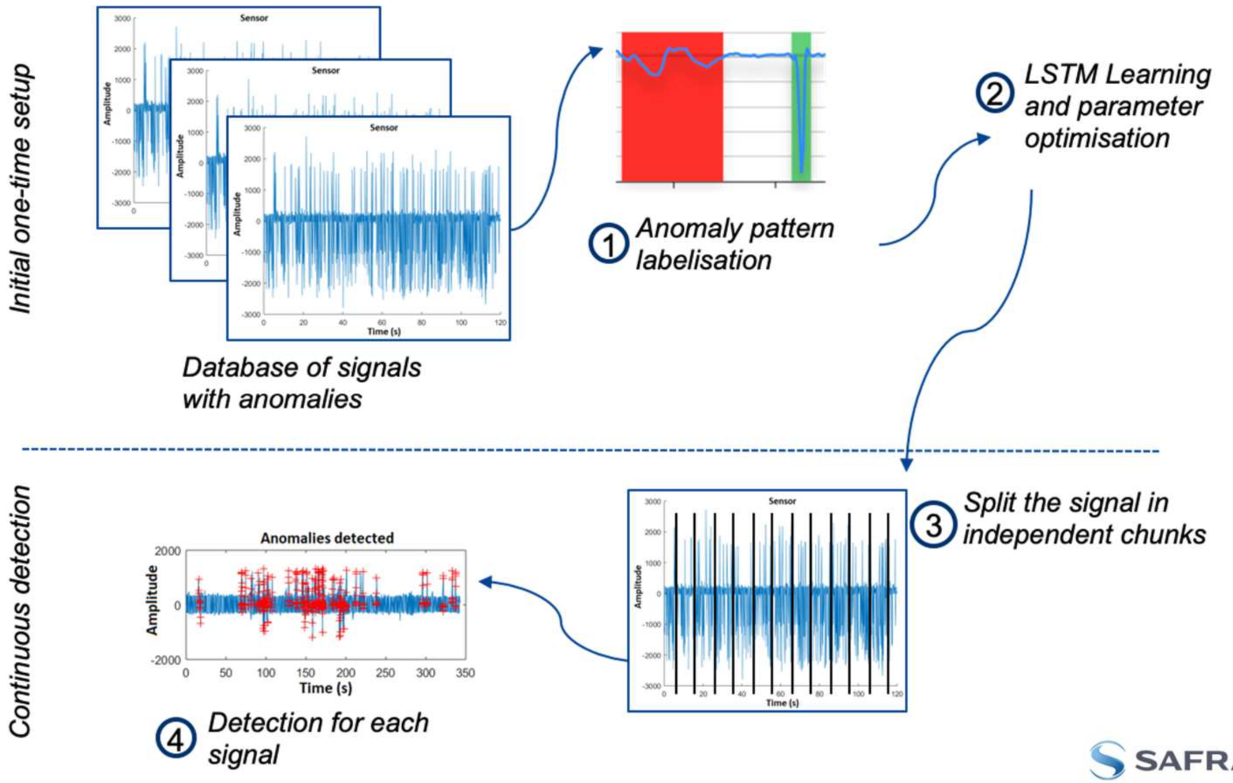
LSTM (1/2)

Long Short Term Memory Autoencoder

- **LSTM Autoencoder**
  - Special type of neural network, generally used to capture the temporal dependencies in time-dependant data;
- **Training phase key points:**
  - Learns to reproduce the behaviour of the portions of sensors data it trained on
  - The ratio of anomalies in the training set is anti-proportional to the model predictive performances
  - Can rely on User expertise to pinpoint the most suitable portions of data for the training
  - Remove obvious anomalies from the training dataset so the model doesn't learn how to reconstruct them
- **Architecture of LSTM proposed by EZAKO :**
  - Encoder/Decoder type architecture
  - LSTM layers in the input/output
  - 4 hidden dense layers
  - 1 code layer
- **Decision function:**
  - Reconstructs the input data, yielding their predictions;
  - Computation of the reconstruction error between the observations and their predictions;
  - Underlying assumption: high reconstruction error for anomalies;
  - Raise an anomaly when the error exceeds the threshold of tolerated error: RE > τ
- **Main advantages : Can retrieve different anomalous patterns**

LSTM (2/2)

Long Short Term Memory Autoencoder

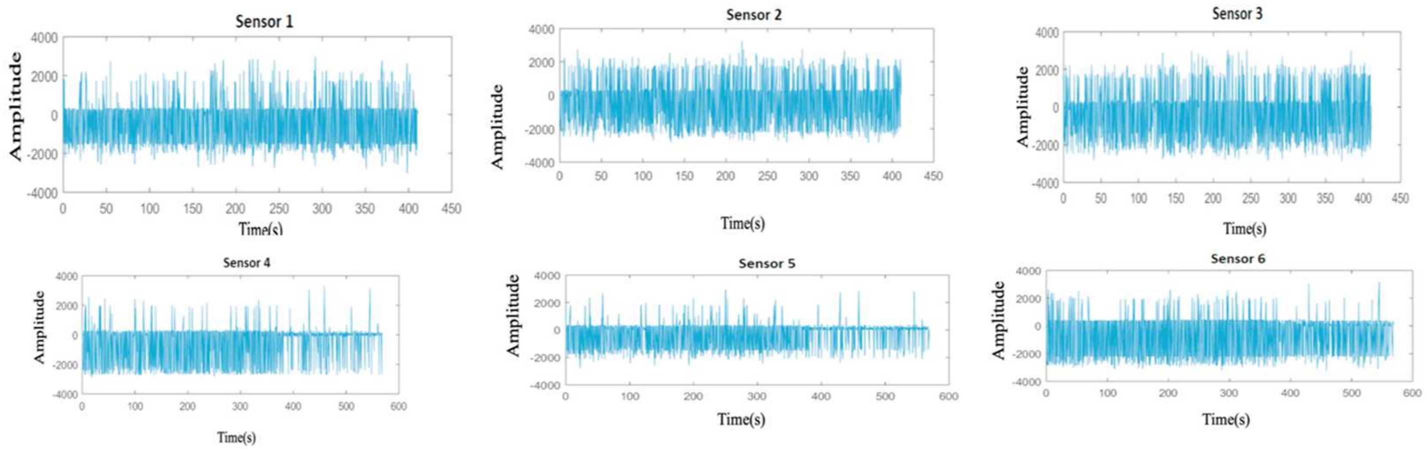


Metrics

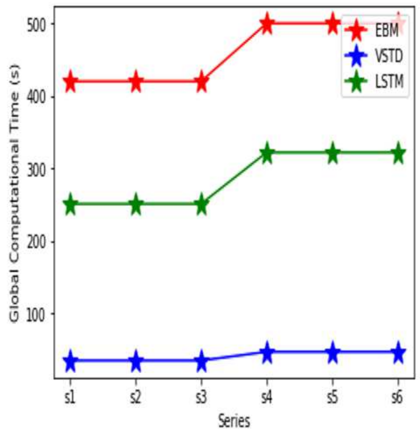
- **Global Computational Time: total amount of time for the detection task;**
- **True Positive Rate: ratio between the number of real anomalies detected and total number of real anomalies;**
- **Precision: classical measure for anomaly detection;**
- **False positive rate: proportion of anomalies detected that represent false positive;**

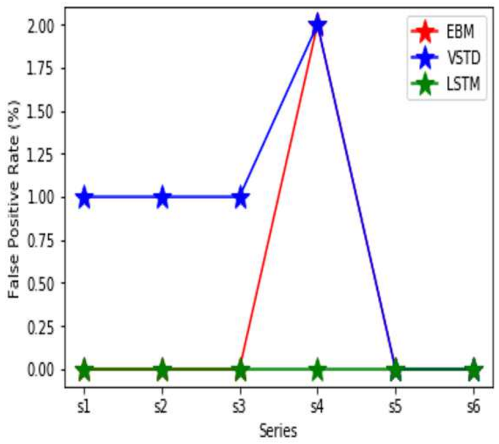
Numerical experiments- Data set

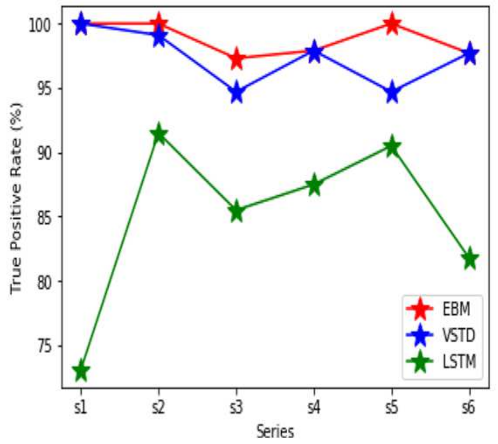
Six signals generated from the gauges of the strain gauges installed on different blades of an engine rotor



Numerical experiments- Results







Legend

- EBM: expert-based method
- VSTD: variant of the standard deviation
- LSTM: long short term memory

Conclusion and perspectives

Conclusion

- Methodological comparison between an expert-based and two new techniques for anomaly detection on plane engines time series;
- Numerical experiments proving that the statistical methods can be 5 to 10 times less burdensome than the expert-based method in terms of computational time.

Perspectives

- Application of the proposed methodology on other types of data.
- Anomalies detection on spectrograms (image processing)

BACK-UP

Numerical experiments: metrics

Methods	Series	Global computational time (seconds)	Precision	True Positive Rate	False Positive Rate
EBM	S1	420	100%	100%	0%
	S2	420	100%	100%	0%
	S3	420	97.3%	97.3%	0%
	S4	500	97.9%	97.9%	2%
	S5	500	100%	100%	0%
	S6	500	97.7%	97.7%	0%
VSTD	S1	35	99.04%	100%	1%
	S2	35	99.1%	99.1%	1%
	S3	35	98.6%	94.7%	1%
	S4	47	97.9%	97.9%	2%
	S5	47	99.7%	94.7%	0%
	S6	47	100%	97.7%	0%
LSTM-AE	S1	251	100%	73.1%	0%
	S2	251	100%	91.5%	0%
	S3	251	100%	85.5%	0%
	S4	322	100%	87.5%	0%
	S5	322	100%	90.5%	0%
	S6	322	100%	81.8%	0%