AI based bridge health assessment

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01 SHM

02 Bridge structure and monitoring network

03 Dynamic identification

04 AI application

05 Conclusions

01. Structural Health Monitoring

Phenomena

Ageing
Fatigue
Corrosion

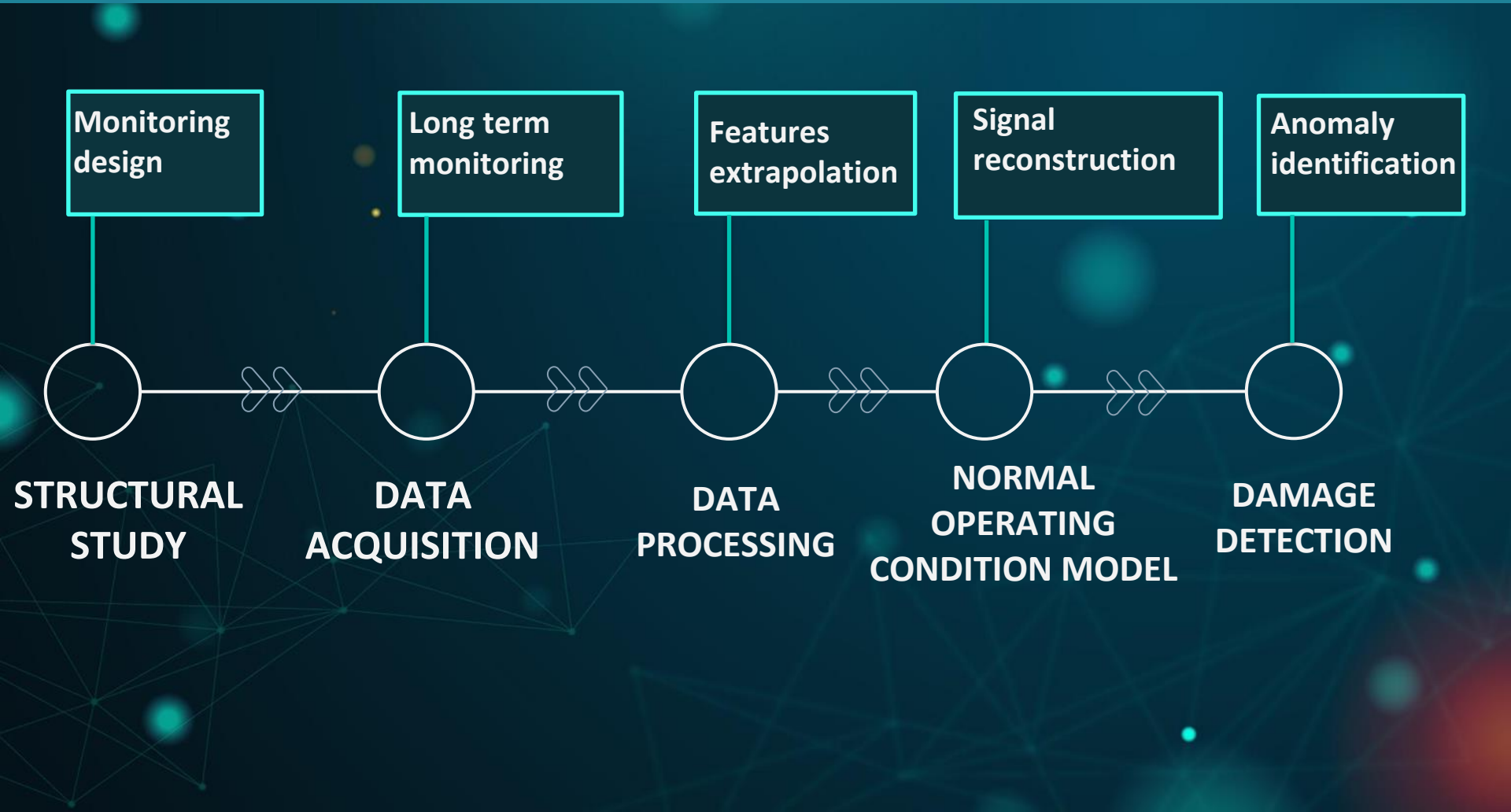
Change of:

Material properties
Structural characteristics
Boundary conditions
Element connectivity

SHM

Check and maintenance strategies

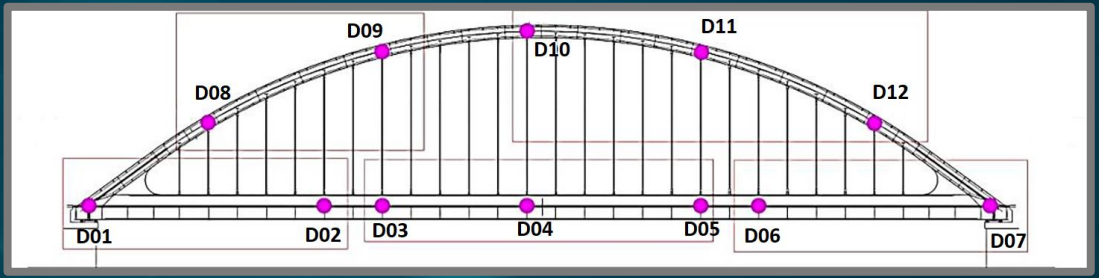
- **Continuous monitoring**
- NDT periodic tests
- Spot tests


Monitoring design
Long term monitoring
Features extrapolation
Signal reconstruction
Anomaly identification
STRUCTURAL STUDY
DATA ACQUISITION
DATA PROCESSING
NORMAL OPERATING CONDITION MODEL
DAMAGE DETECTION

02. Bridge structure

- Highway steel suspended arch bridge
- Span: 250 meters
- 25 steel hangers

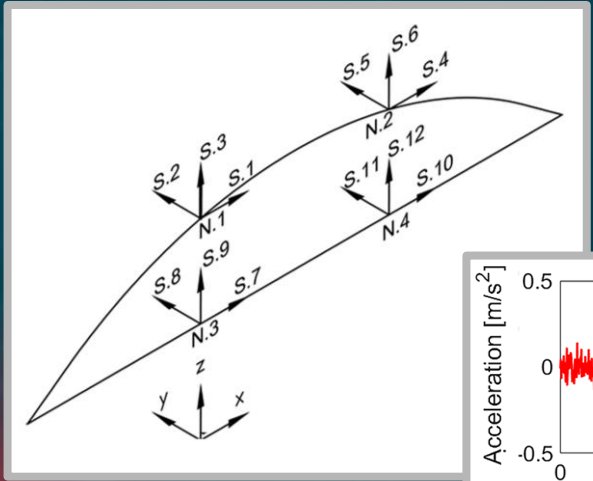
02. Monitoring network

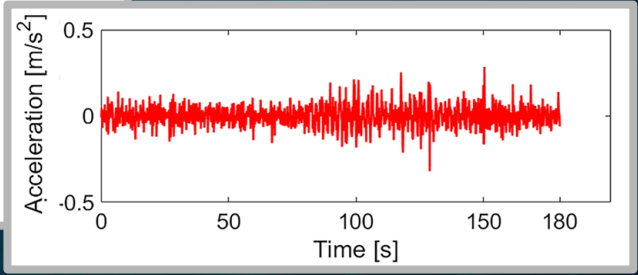


5 measuring stations

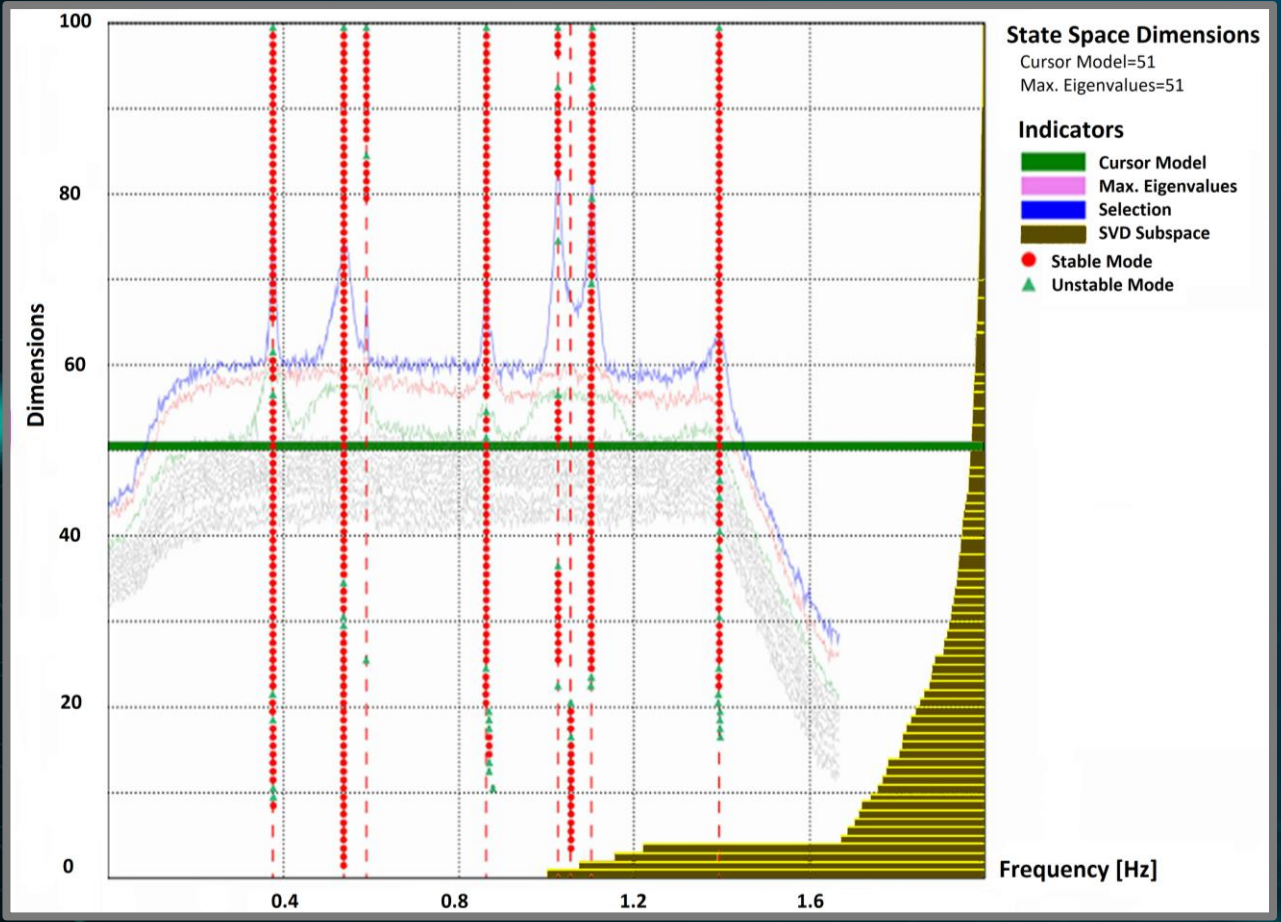
Fiber optic

Control room





03. Dynamic identification



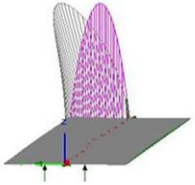
OMA

Software: **ARTeMIS**

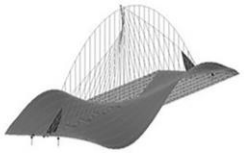
Algorithm: **SSI-UPCX**

Modal parameter and uncertainty extraction

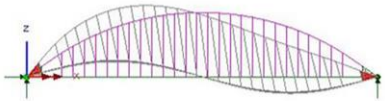
Mode shapes



Mode 1 (f1= 0.37Hz)
Bending out plan



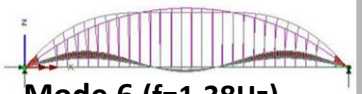
Mode 4 (f4= 1.04Hz)
Out of the plane double inflection



Mode 2 (f2= 0.53Hz)
Double vertical inflection

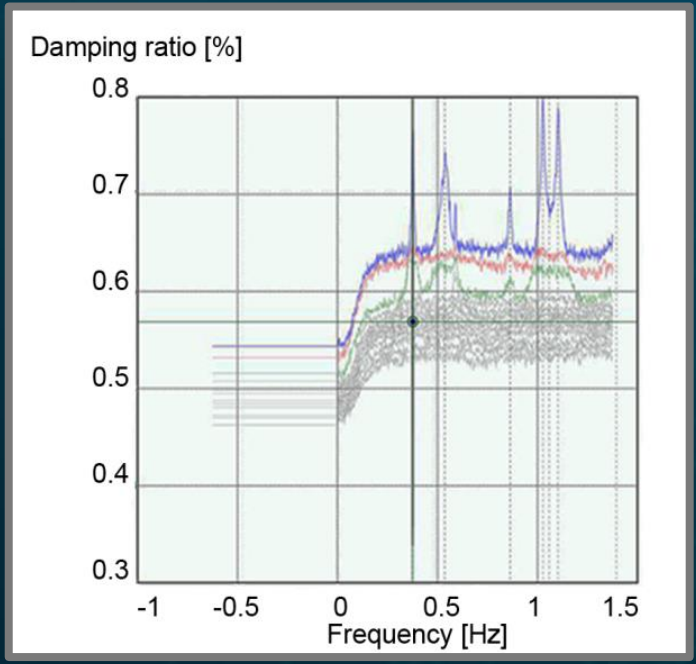
Mode 5 (f= 1.09Hz)
Torsional

Mode 3 (f3= 0.85Hz)
Single vertical inflection

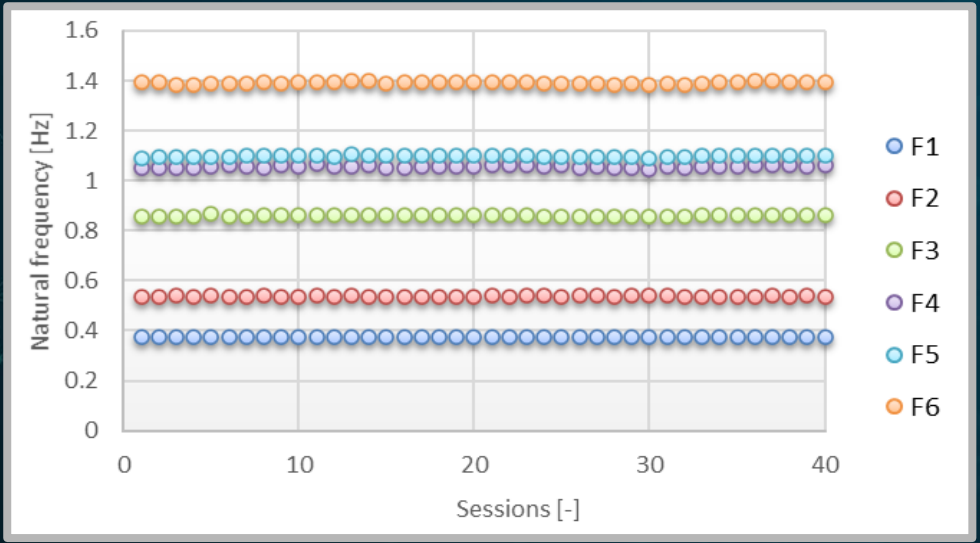


Mode 6 (f=1.38Hz)
Triple vertical inflection

Frequency vs. Damping and confidence interval



Vibration Mode	Mode1: BENDING Out of plane	Mode2: Double vertical inflection	Mode3: single vertical inflection	Mode4: out of plane double inflection	Mode5: torsional	Mode6: triple vertical inflection
Frequency	F1	F2	F3	F4	F5	F6
F_Min [Hz]	0.373	0.532	0.856	1.044	1.091	1.383
F_Max [Hz]	0.3772	0.540	0.866	1.065	1.105	1.400
Var Rel [%]	1.069	1.398	1.167	1.979	1.239	1.238



DAMAGE LEVELS	DEGREE OF SEVERITY	SIGNAL VARIATION	FREQUENCY	F1	F2	F3	F6
			FA[%]	0.0	12.5	0.0	0.0
LD7	LOW	~0.33%	MA[%]	75.0	97.9	62.5	70.8
LD8	MEDIUM-LOW	~0.66%	MA[%]	41.6	75.0	27.1	39.6
LD9	MEDIUM	~1.0%	MA[%]	2.1	35.4	2.1	8.3

Nd: number of data identified as damaged

Nud: number of data identified as undamaged

Ntest_ud: number of undamaged data

Ntest_d: number of damaged data

False alarm	Missing alarm	Total alarm
$FA = \frac{N_d}{N_{test\_ud}} \cdot 100$	$MA = \frac{N_{ud}}{N_{test\_d}} \cdot 100$	TE=FA+MA

Combination F1-F3-F6	MA [%]	FA [%]	TE [%]
LD7	58.3	0.0	58.3
LD8	18.8	0.0	18.8
LD9	0.0	0.0	0.0

04. AI application

K-means algorithm

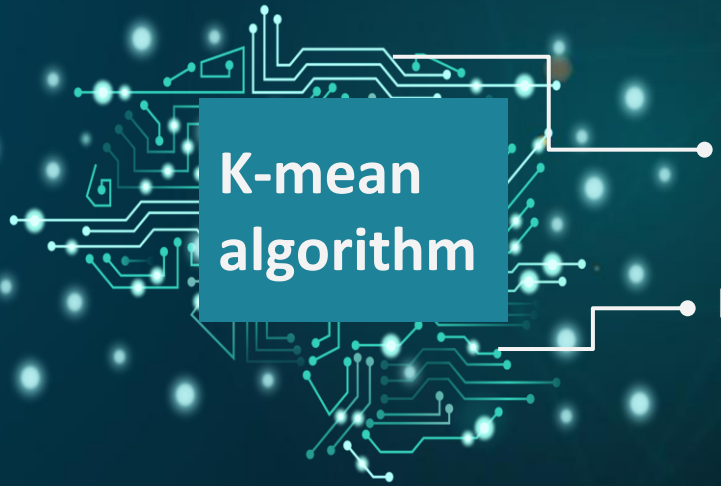
- Unsupervised learning algorithm
- Partitional clustering approach

Lloyd approach

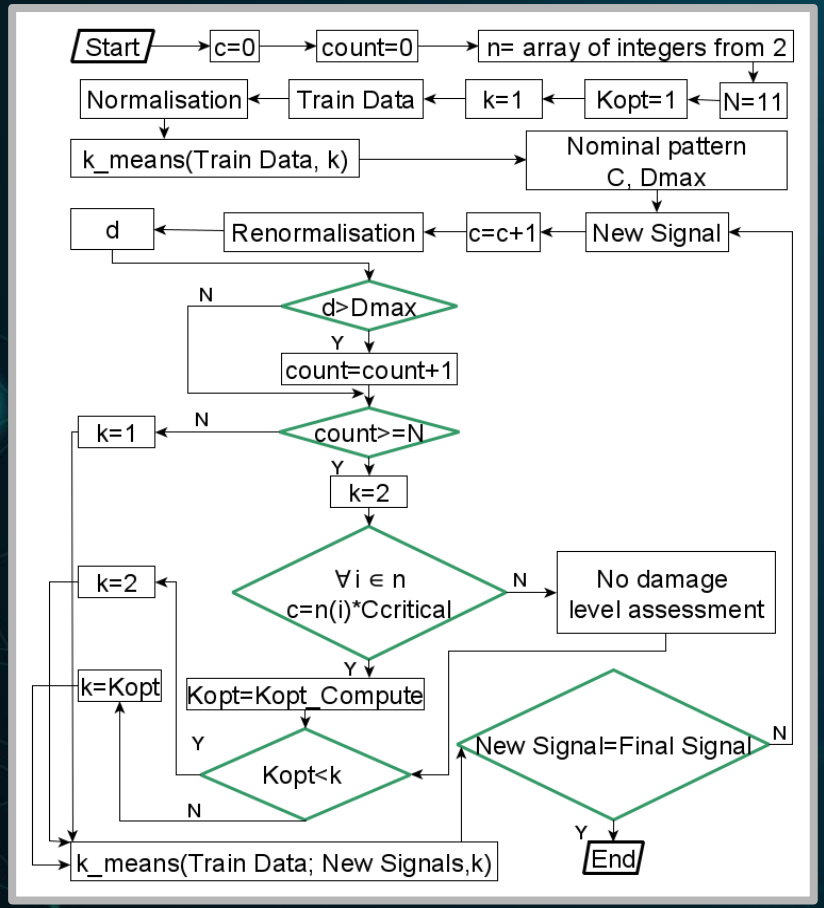
1. Choice of k centroids
2. Assign each signal to the closest cluster centroid
3. Calculate the new k point centers

Applicative aspects

1. K-means++algorithm for k initial cluster centroid
3. Squared Euclidean distance as distance metric
4. ‘Replicates’
5. Data normalization (Min-Max)



Tracking of structural changing



C= centroid of nominal patter

Dmax= maximum distance from C (nominal pattern)

d= distance new signal-nominal centroid

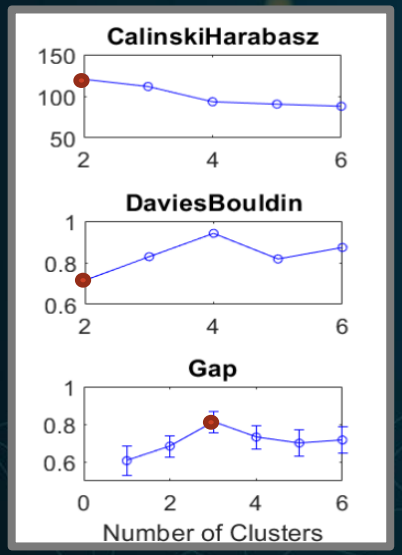
count= number of signals with (**d**> **Dmax)**

N= persistence number

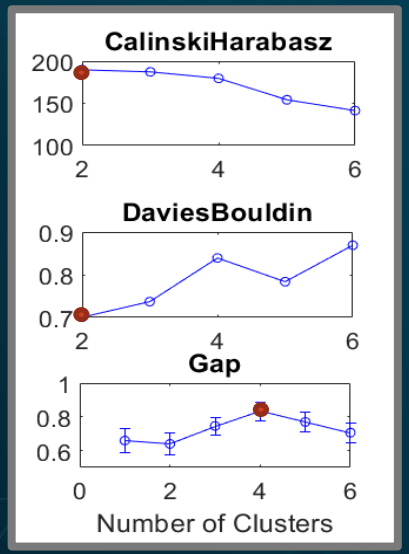
Ccritical= number of signals in a critical time unit

Kopt= optimal number of clusters

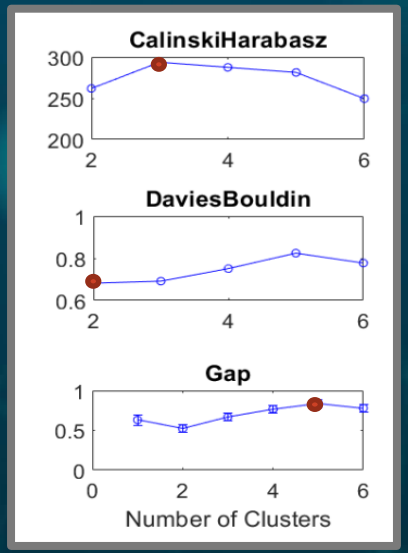
Recognition of increasing damage (LD7-LD8-LD9)



First unit

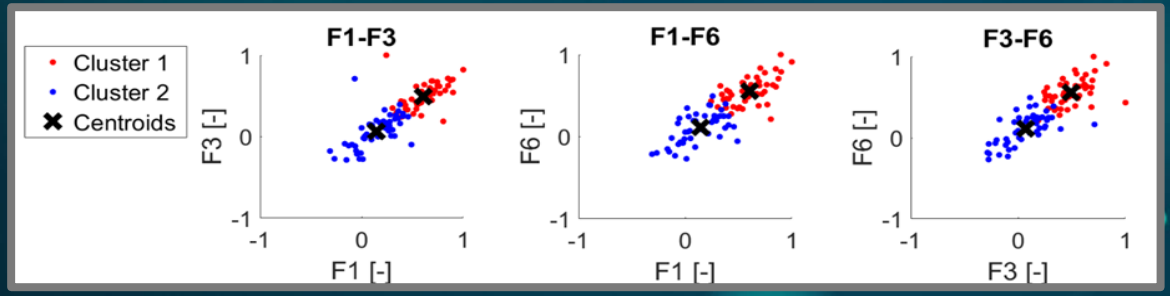


Second unit

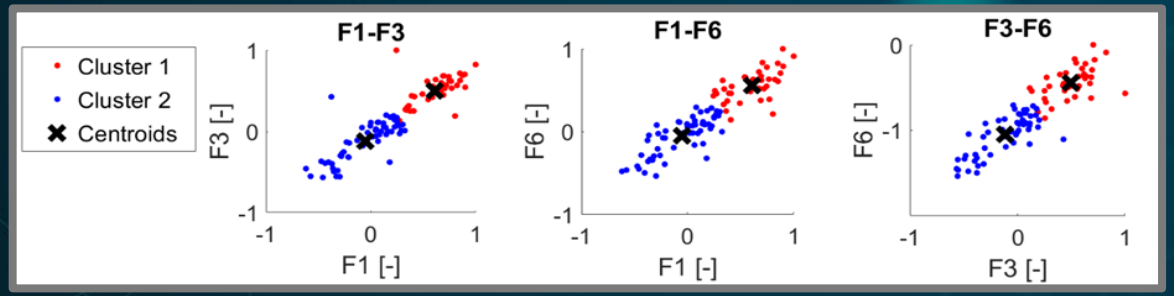


Third unit

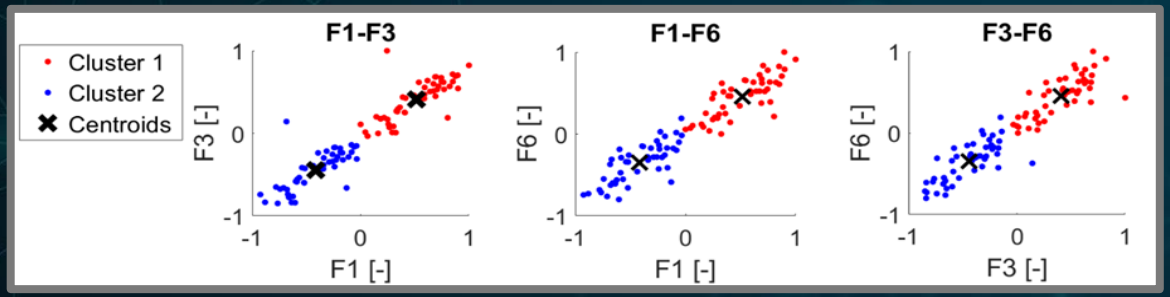
Dataset 1
Test_Ud
and LD7



Dataset 2
Test_Ud
and LD8



Dataset 3
Test_Ud
and LD9



Damage detection capacity

Dataset 1
Test_Ud and LD7

29.1% (MA)

Dataset 2
Test_Ud and LD8

4.1% (MA)

Dataset 3
Test_Ud and LD9

2.1% (MA)

Better results with kopt for **EARLY-STAGE DAMAGE LEVELS (Dataset 1)**

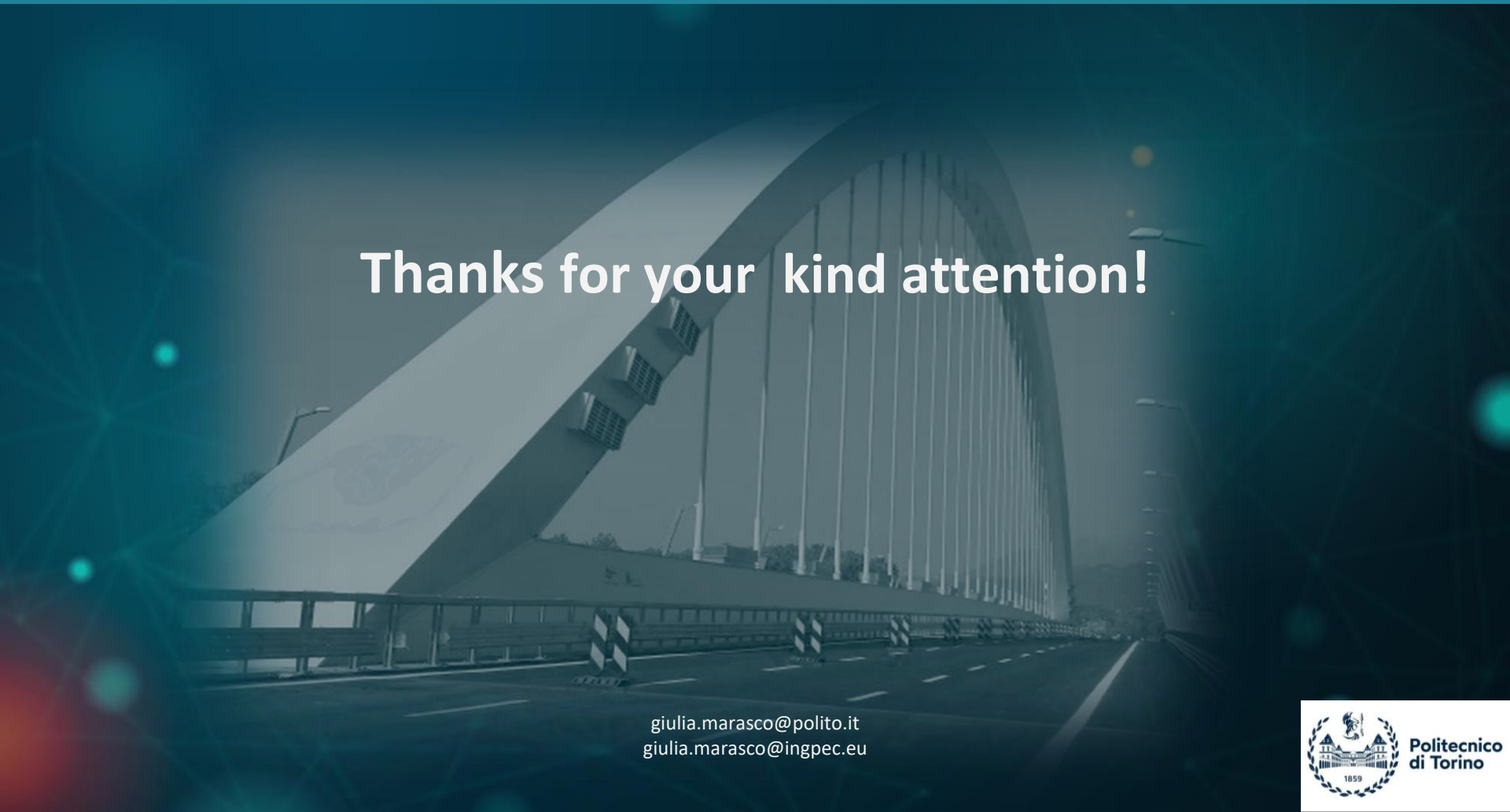
6.25% (MA)

05. Conclusions

- The traditional approach shows a very low detection capability of damaged signals (weak signals are not identified).
- For small damage levels, the clustering technique has a better damage detection performance.
- For small damage level, an increased computational effort in the calculation of the optimum value of numbers of clusters produces a further improvement as regards MA.
- Possibility to observe the evolution of the optimal number of clusters for assessing the increase of damage.

Perspectives

- A greater quality of data would imply an improvement of the clustering algorithm performance.
- Investigation on the role of the persistence number and the optimal number of clusters
- Research of more performant features



Thanks for your kind attention!

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