

# Al-Enhanced Condition Monitoring of Railway Infrastructure Using Onboard and Wayside Systems

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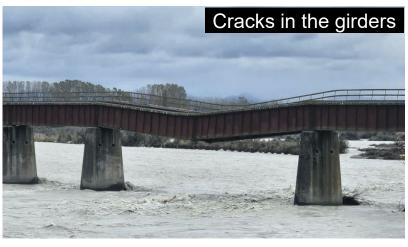
# **Contents**

- 1. Introduction
- 2. Al-based damage identification methodology
- 3. Onboard monitoring systems
- 4. Wayside monitoring systems
- 5. Conclusions

## 1. Introduction

#### **Bridge & track damages**







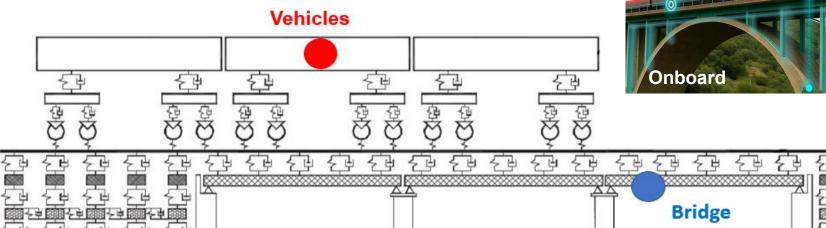
Crack in the pier



#### 1. Introduction

#### **Onboard vs direct monitoring**

#### **Condition monitoring strategies**



V2V (Vehicle-to-Vehicle)
V2I (Vehicle-to-Infrastructure)

Track



**I2V** (Infrastructure-to-Vehicle)

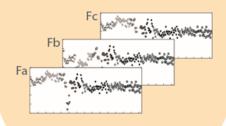
**121** (Infrastructure-to-Infrastructure)



# 2. Al-based damage identification methodology

#### **Overview**

# FEATURES EXTRACTION



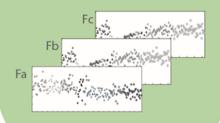
#### **CLASSIC METHODS**

Basic Modal Properties Statistical features

#### **ADVANCED METHODS**

Time Series Models
(AR, ARX)
Continuous Wavelet
Transform (CWT)
Principal Component
Analysis (PCA)
Mel-frequency cepstral
coefficients (MFCC)

# FEATURES NORMALIZATION



#### INPUT-OUTPUT

Multivariate Linear Regression (MLR)

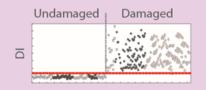
#### **OUTPUT-ONLY**

Principal Component Analysis (PCA)

#### DATA FUSION



## FEATURES CLASSIFICATION



# Mahalanobis Distance (MD)

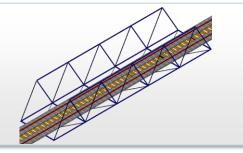
1st level – features fusion 2nd level – sensors fusion 3rd level – different type of data fusion (acceleration, strains, etc.) Outlier Analysis (statistical threshold)

**Cluster Analysis** 

**Use cases** 

Degradation in a Warren truss bridge

**Numerical** 



Track degradation in Ferrovia Tereza Cristina (Brazil)

**Experimental** 



**Degradation in a Warren truss bridge** 

#### Main challenges

- Ability to detect damage on bridges using the dynamic responses of freight service vehicles with operating speeds typically less than 100 km/h.
- Use of experimentally calibrated numerical models for the bridge and vehicle.
- Introduction of damage in primary and secondary components for more precise identification and efficient maintenance.
- Consideration of a broader range of EOVs.









#### **Degradation in a Warren truss bridge**

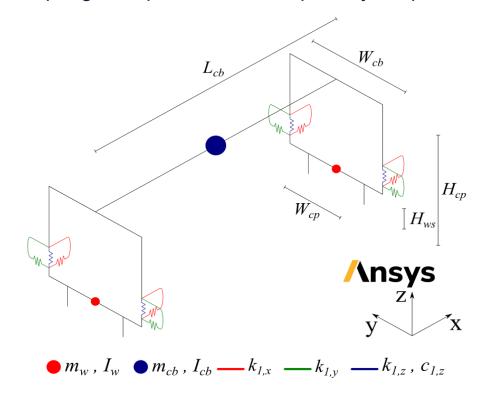
#### Freight vehicle

- Laargss freight wagon for container transportation
- Total length: 14.8 m
- 2-axles spacing 10 m
- 4-sets of progressive stiffness parabolic springs
- Max. load capacity: 52 t

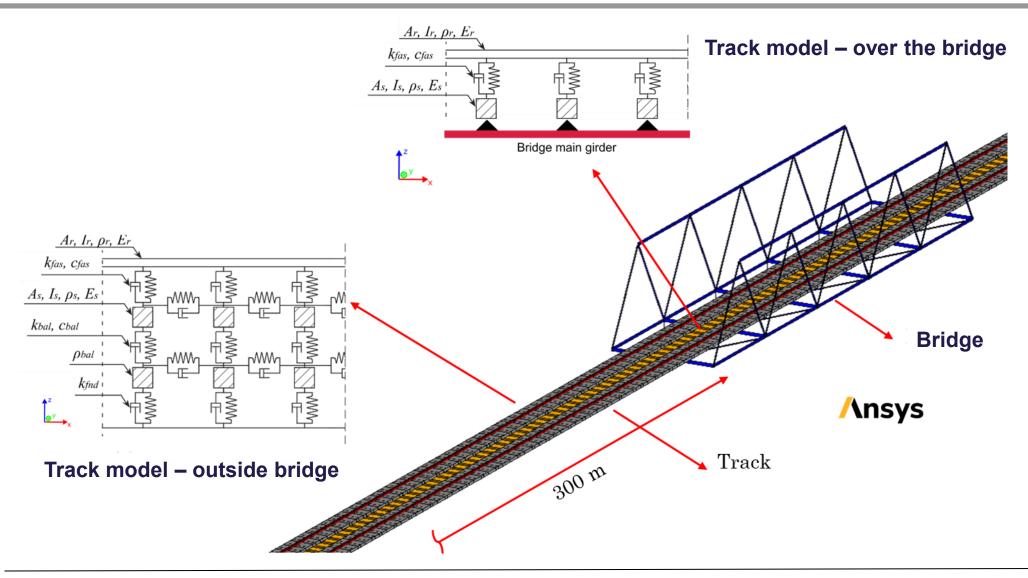


#### **Numerical model**

- 3D rigid body model
- Rigid bars: platform and axles
- Spring-dashpot assemblies: primary suspensions



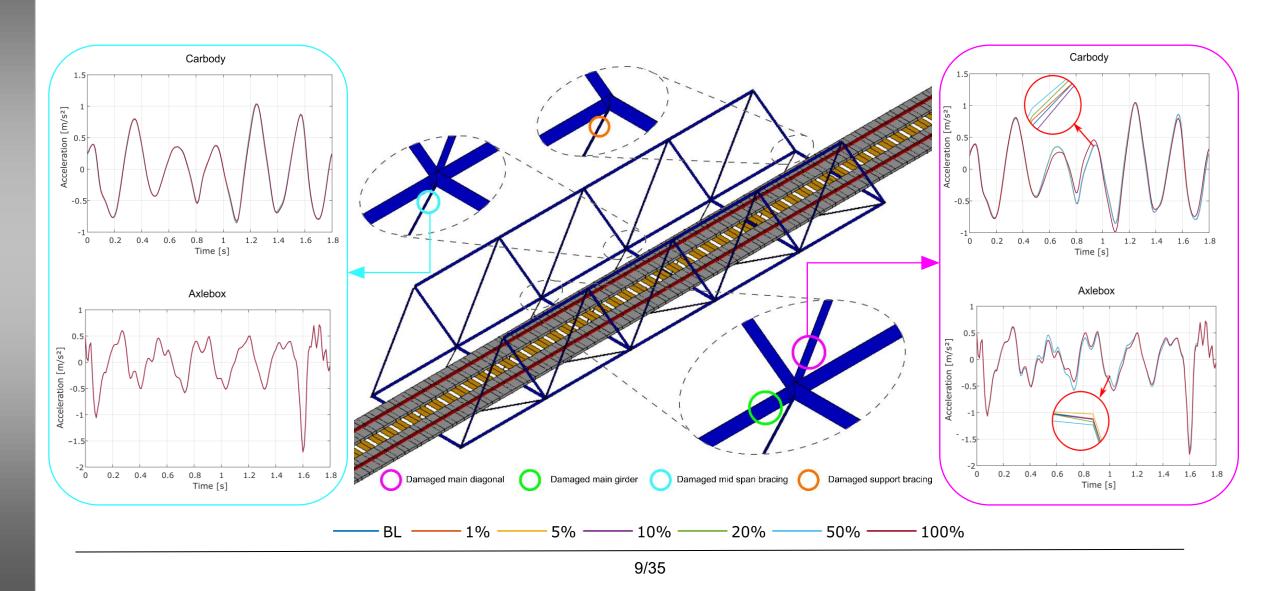
**Degradation in a Warren truss bridge** 



# **Degradation in a Warren truss bridge**

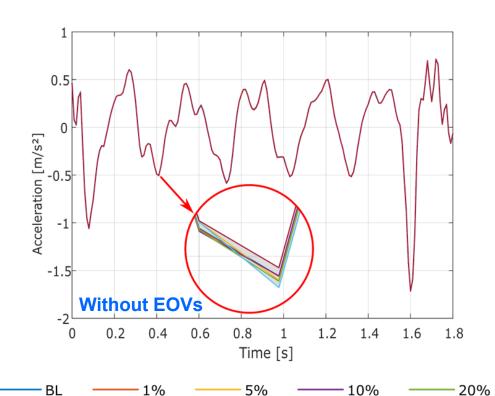
Condition	Baseline		
	Undamaged	Slightly damaged	Damaged
LAAGRSS type wagons	5	5	5
Speeds (km/h)	45/50/55	45/50/55	45/50/55
Irregularity profiles	2	1	1
Wagon mass variation (%)	90/95/100/105/110	90/95/100/105/110	90/95/100/105/110
Change in modulus of elasticity w/ temperature (‰)	975/1000/1025	975/1000/1025	975/1000/1025
Positioning accuracy (m)	±1	±1	±1
Measurement noise (%)	5	5	5
Damage severities (%)	-	< 0.5	1/5/10/20/50/100
Individually damaged elements	-	4	4
Number of simulations	90	1,260	1,080 (4x270)

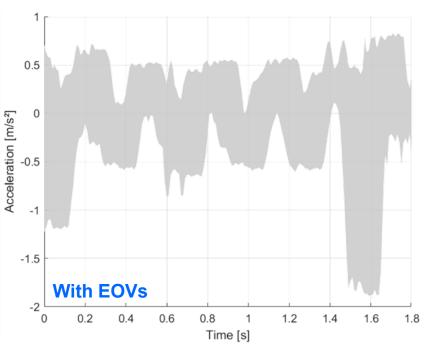
## **Degradation in a Warren truss bridge**



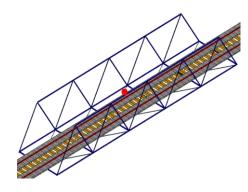
#### **Degradation in a Warren truss bridge**

Challenge of removing the **influence of operational and environmental variabilities** from the carbody's dynamic response





100%



#### **EOVs**

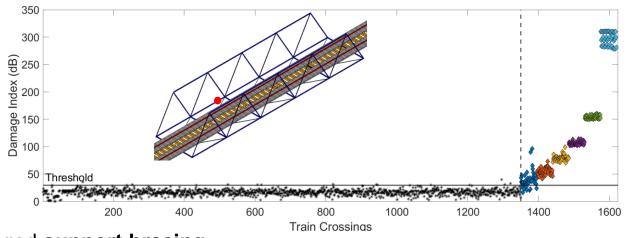
Envelope of responses

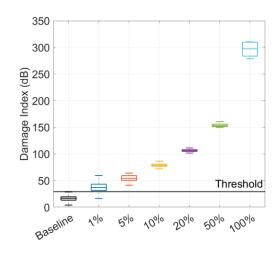
- Train speed
- Irregularity profiles
- Wagon mass variations
- Temperature
- Positioning accuracy
- Measurement noise
- Manufacturing imperfections

50%

## **Degradation in a Warren truss bridge**

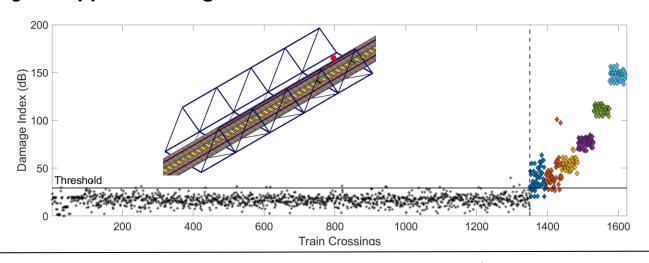
#### Damaged main girder

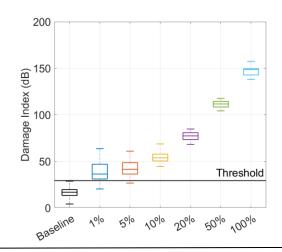






#### Damaged support bracing





Track degradation in Ferrovia Tereza Cristina (Brazil)

#### **Track information**



General information

Location: South of Brazil

**Built in: 1953** 



**Gauge:** 1,000 mm

Sleepers: Wooden

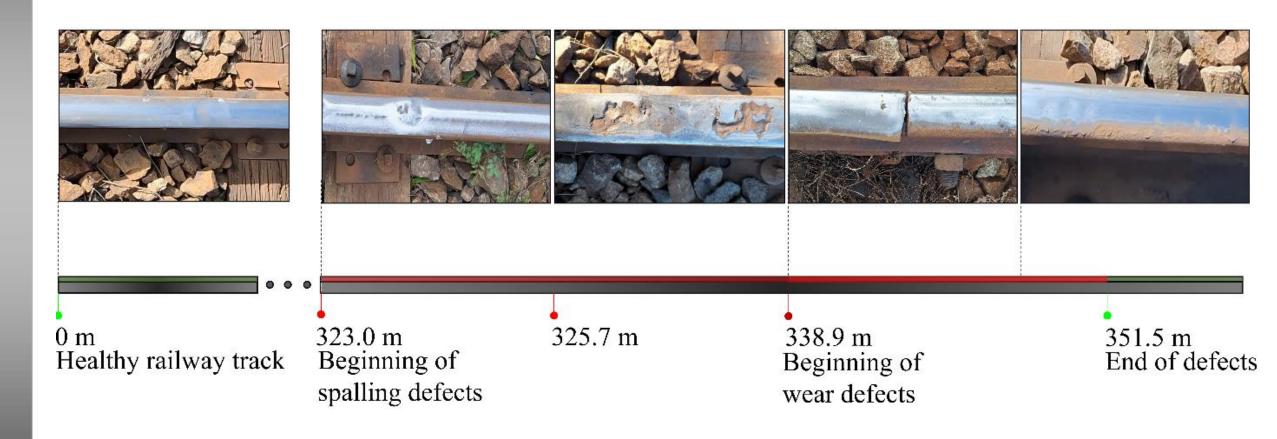
Foundation: Ballasted track



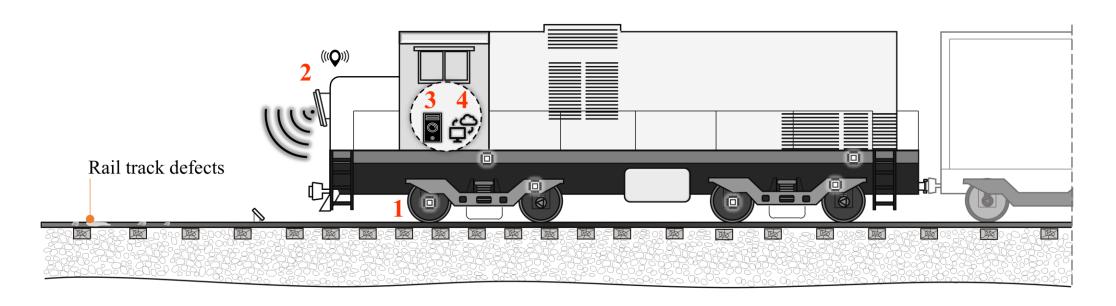


Track degradation in Ferrovia Tereza Cristina (Brazil)

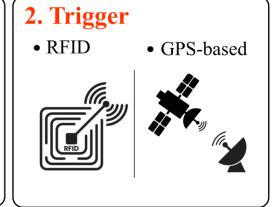
#### **Track damages**



Track degradation in Ferrovia Tereza Cristina (Brazil)

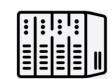


# 1. Sensors12 uniaxial accelerometersCar body, bogies and axle box placements



#### 3. Data Acquisition

- Modular system inside of locomotive (16 channels)
- 1 kHz sampling rate

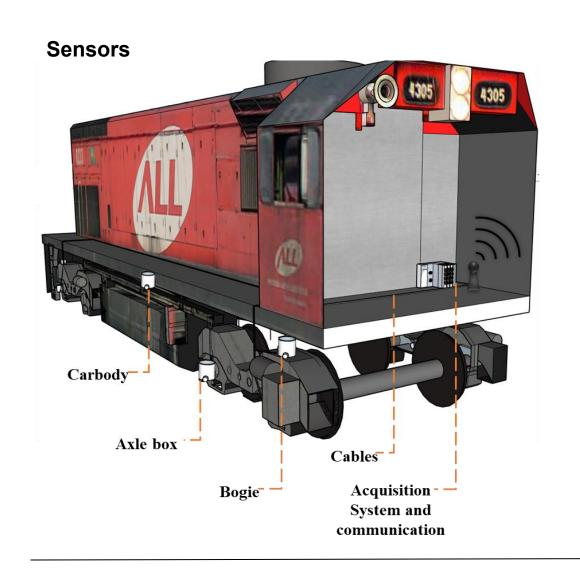


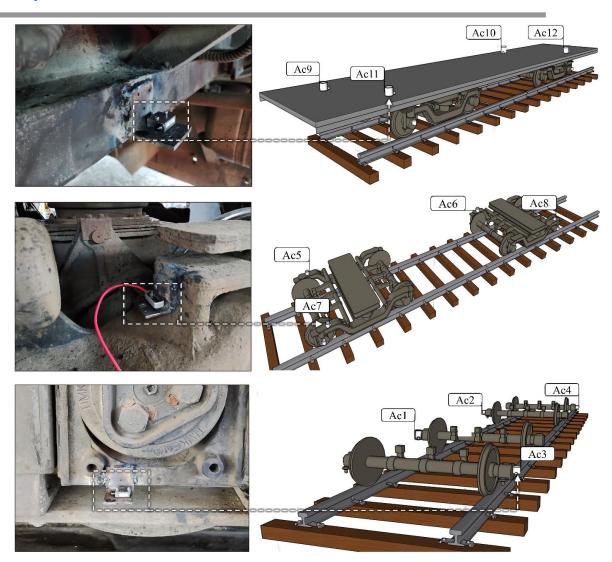
#### 4. Communication

- 3G and Wi-fi antennas
- Cloud storage
- Remote access
- GPS tracking









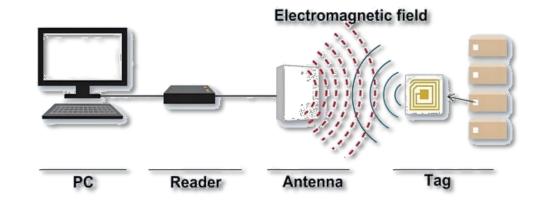
Track degradation in Ferrovia Tereza Cristina (Brazil)

**Communication system:** 3G Modem, WiFi antenna, cloud storage service & remote desktop service

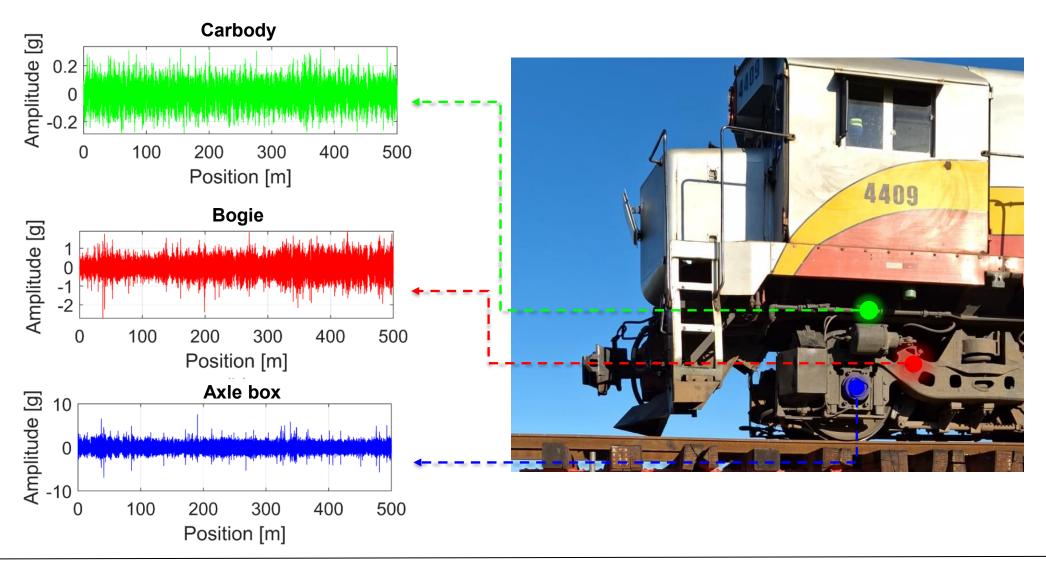
Tracking system: GPS

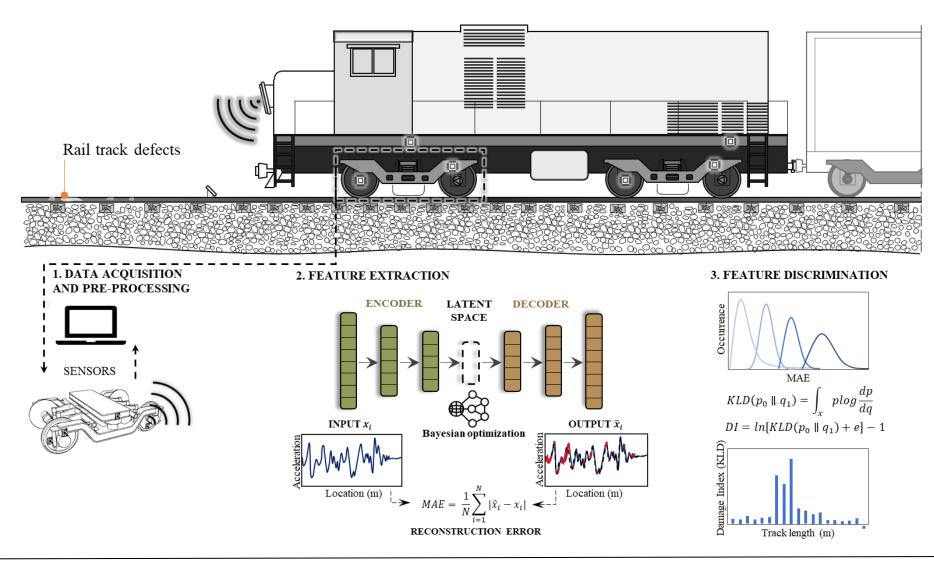
**Trigger system:** data logging & speed estimation

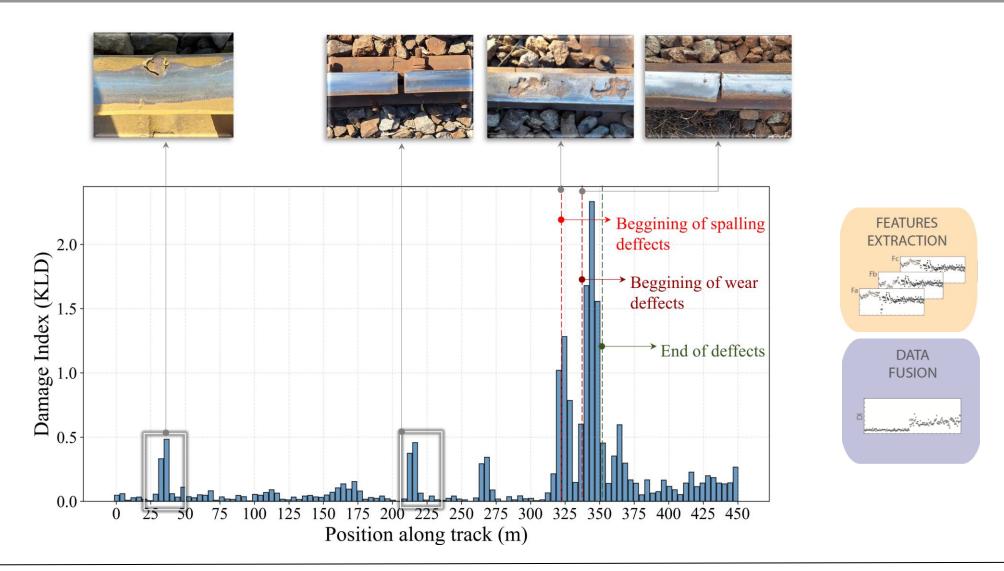












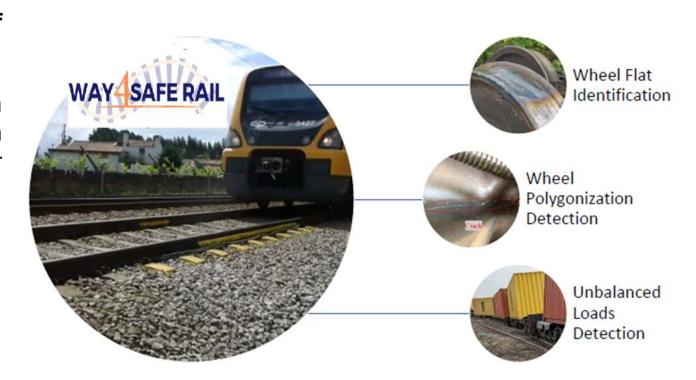
Way4SafeRail project

Way4SafeRail project envisage the design of a l2V wayside monitoring system capable of:

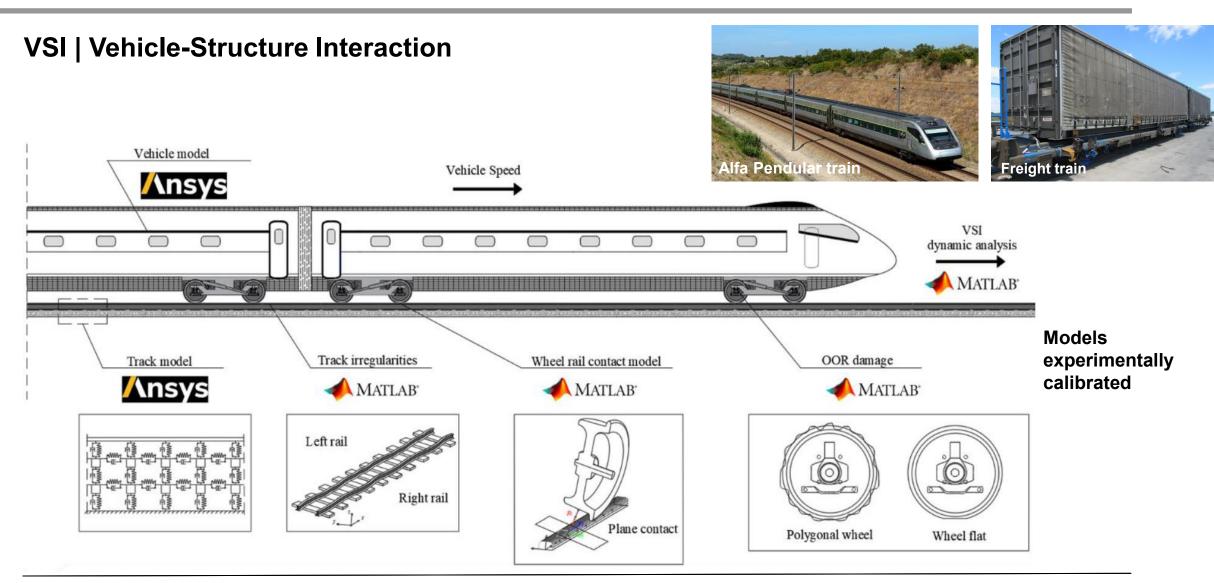
- i. assessing the condition of the train wheels (flats and polygonization) in operation, monitoring and categorizing their severity
- ii. detecting situations of instability in railway circulation, particularly **unbalanced loads**



WAY4SAFERAIL project consortium

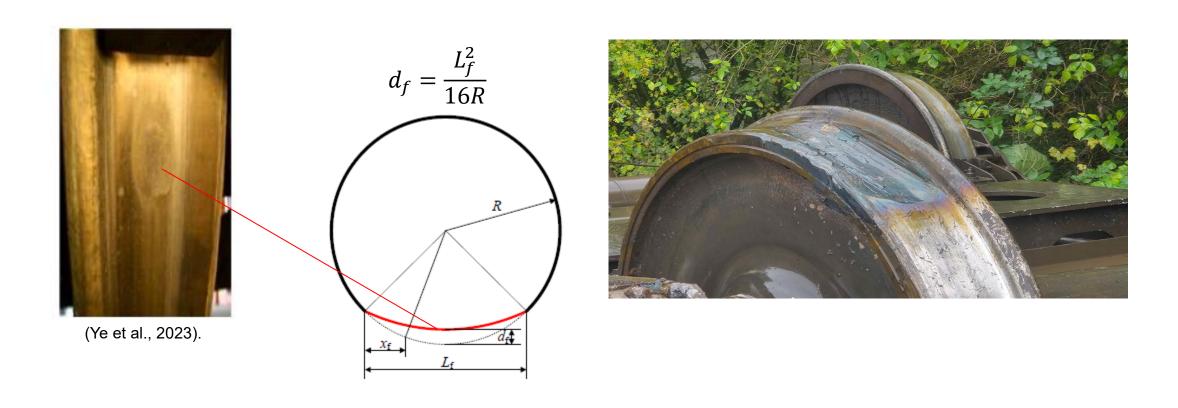


**Train-track dynamic interaction** 



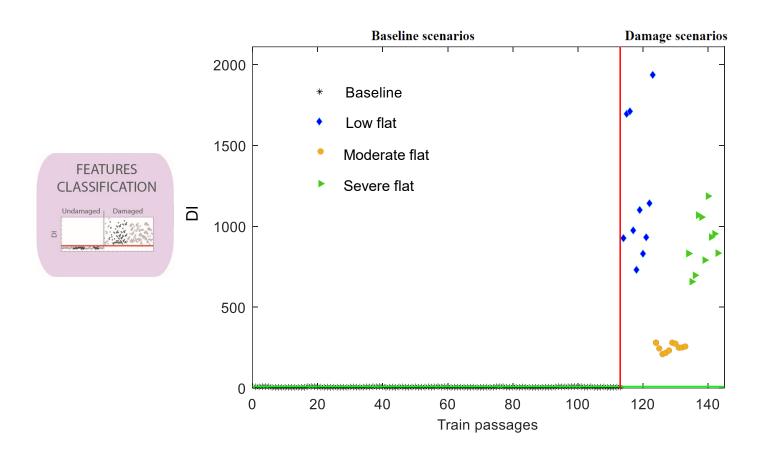
#### Wheel flat

Wheel flat is a common tread defect mainly caused by repeated wheel/rail abrasion during the braking and the rolling of wheels over a long period of time.



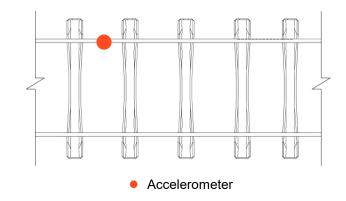
#### Wheel flat

## Wheel flat detection: Outlier Analysis using Auto Regressive model features



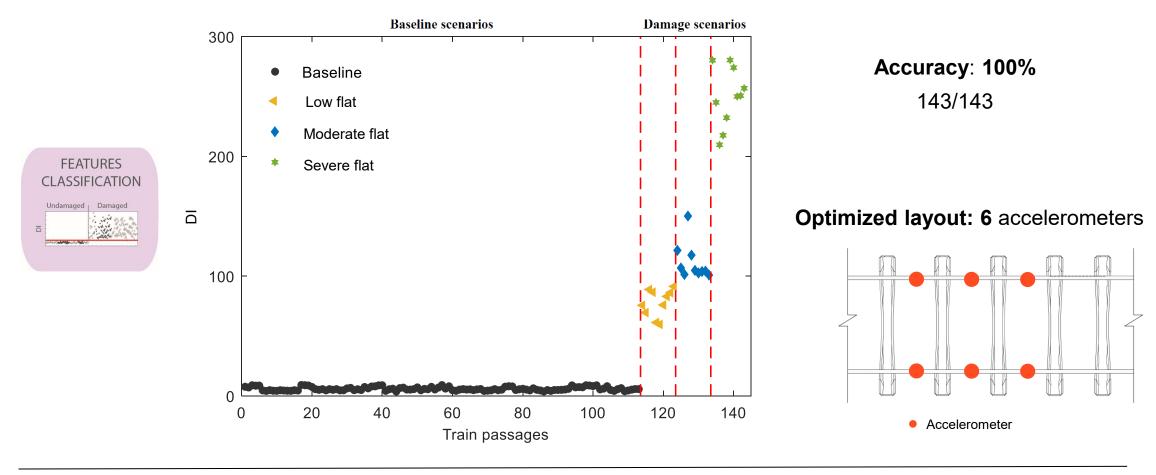
**Accuracy**: **100%** 143/143

**Optimized layout: 1** accelerometer



#### Wheel flat

## Wheel flat classification: Cluster Analysis using Auto Regressive model features

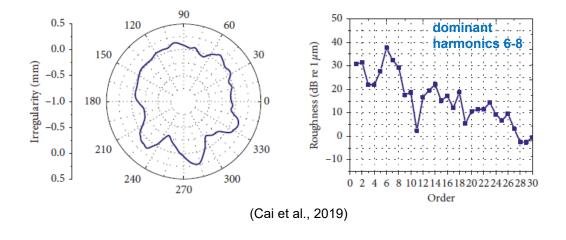


## **Polygonal wheels**

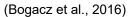
The **wheel polygonalization** is a periodic radial irregularity or wear around the wheel circumference with wavelength larger than 140 mm and amplitudes > 0.2 mm.

	Wavelength	Amplitude
Roughness	30-80 mm	10 μm
Polygonization	140 mm-one circle	>0.2 mm

(Peng, 2020)





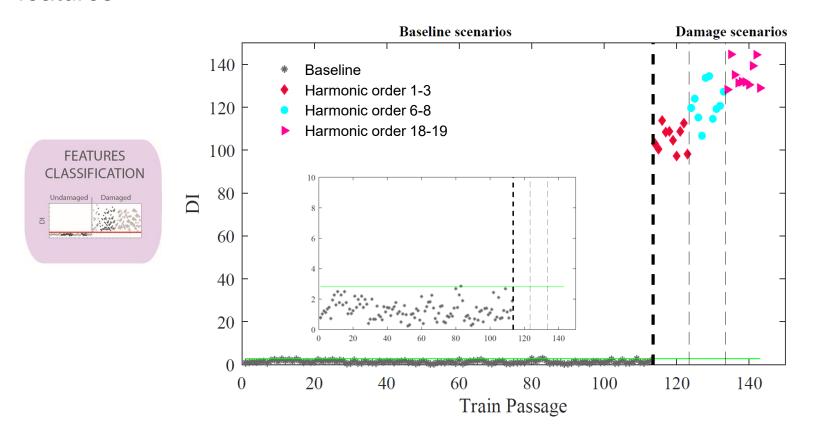




(Wu et al., 2020)

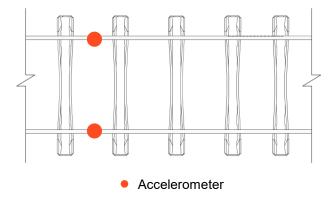
#### **Polygonal wheels**

**Polygonalization detection**: Outlier Analysis using AutoRegressive eXogenous (ARX) model features



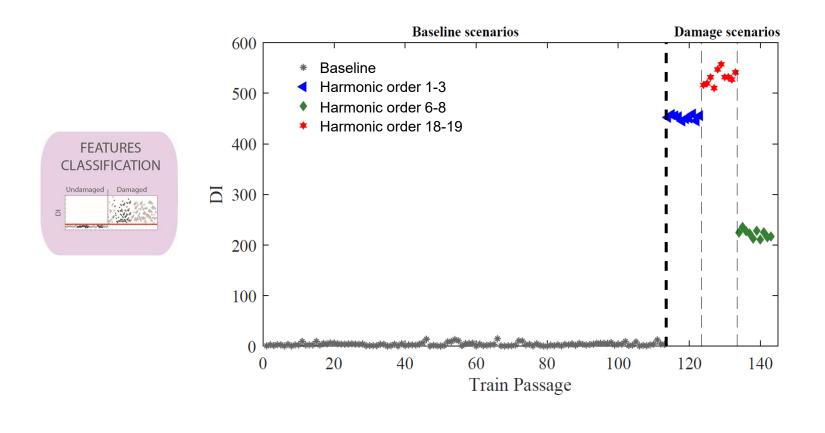
Accuracy: 99.3% 142/143 1 false positive

**Optimized layout: 2** accelerometers



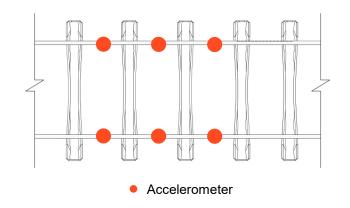
#### **Polygonal wheels**

## Polygonalization classification: Cluster Analysis using PCA & CWT model features



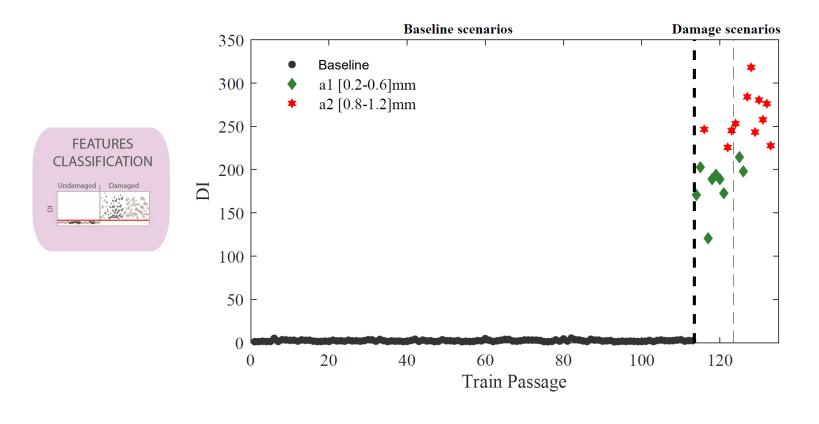
**Accuracy**: **100%** 143/143

**Optimized layout: 6** accelerometers



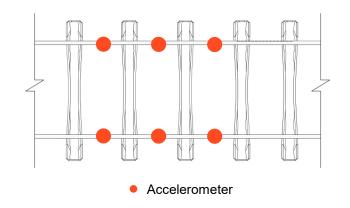
#### **Polygonal wheels**

**Polygonalization classification**: Cluster Analysis using AutoRegressive eXogenous (ARX) model features



**Accuracy**: **96.2%** 128/133

**Optimized layout: 6** accelerometers

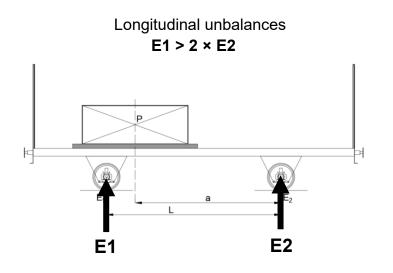


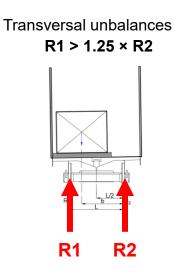
#### **Unbalanced loads**

The presence of unbalanced loads on freight trains can potentially cause higher levels of deterioration or even the failure of railway track components, as well as situations of risk of derailment

For **2-axle wagons**: ratio of **2:1** between the masses per axle

For **all wagons**: ratio of masses per wheel: 1.25:1



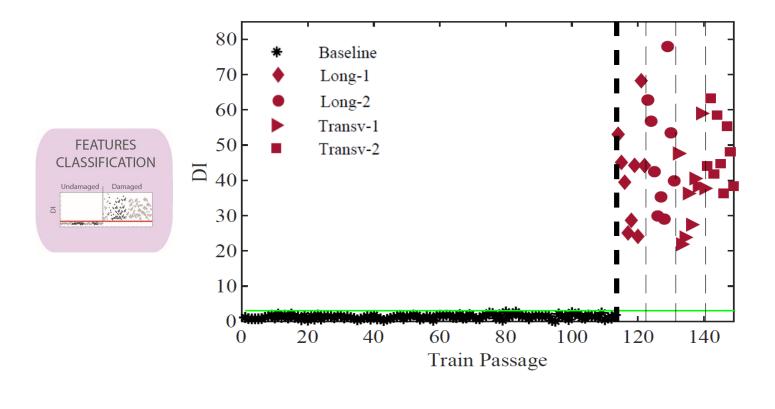






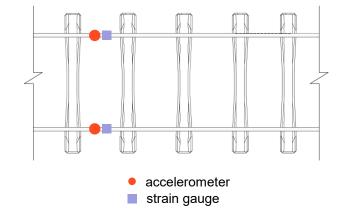
#### **Unbalanced loads**

**Unbalanced loads detection:** Outlier Analysis using AutoRegressive eXogenous (ARX) model features



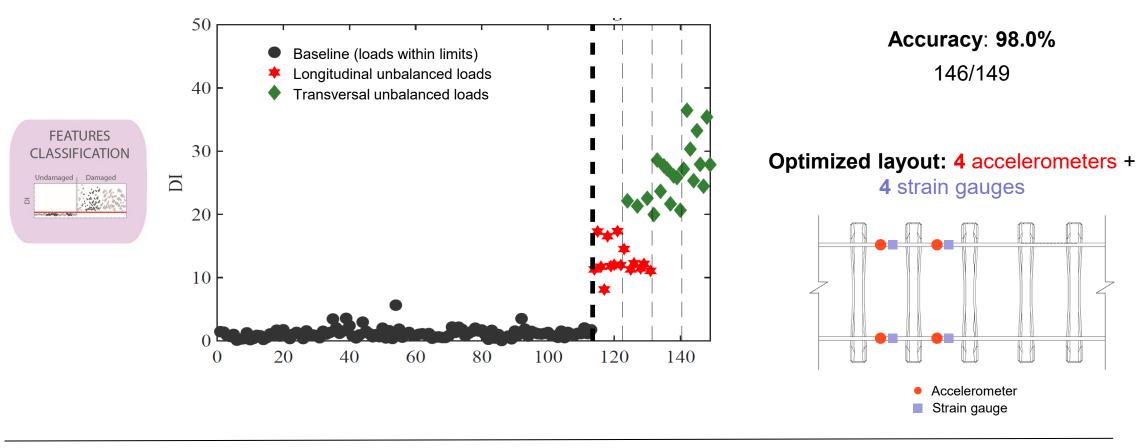
**Accuracy**: **98.7%** 147/149

Optimized layout: 2 accelerometers + 2 strain gauges



#### **Unbalanced loads**

## Unbalanced loads classification: Cluster Analysis using PCA features



## **Experimental campaign**



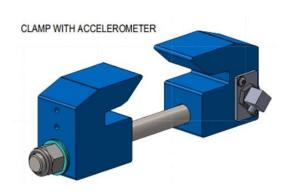


6 Accelerometer ICP Model 356A02



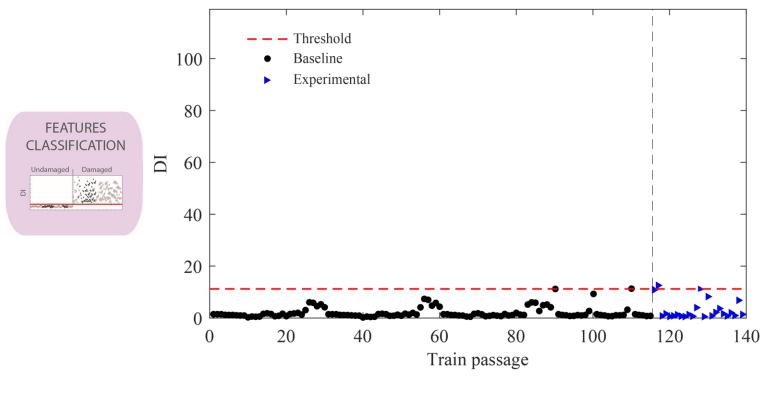
4 Strain Gages LEA-06-W125E-350/3R



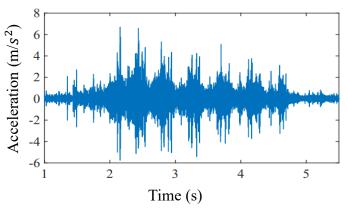


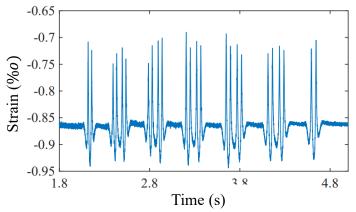
## **Experimental campaign**

## Polygonalization classification: real-time online procedure









#### 5. Conclusions

- Al-based condition monitoring of railway infrastructures based on vibration data is an ongoing and challenging research topic, however, already constitutes an efficient and cost-effective health monitoring strategy.
- The most recent damage identification methodologies are based on advanced feature extraction, data normalization to remove the influence of EOVs, multi-fusion processes to enhance the sensitivity to damage, and damage classification based on statistical approaches.
- Most of the existing research is based on numerical strategies and the experimental validation of the proposed damage identification strategies are still ongoing. This is a key step to ensure that the methodology is robust and ready to address the complexities of real-world applications.
- The use cases presented in this work proved the efficiency of the proposed methodology on onboard and wayside applications under demanding operational scenarios, namely for bridges and track sections located on freight and regular traffic lines.
- In both cases the methodology had a very good performance in detecting and classifying early-stage individual damages in bridge structural elements, detecting track defects and characterizing critical safety situations on moving trains.
- Future works include upgrades on the methodology to properly localize the damages, as well as, working on multiple-damage scenarios. Also, the continuation/upgrade of experimental campaigns/results is a priority action.

# **Acknowledgements**











