

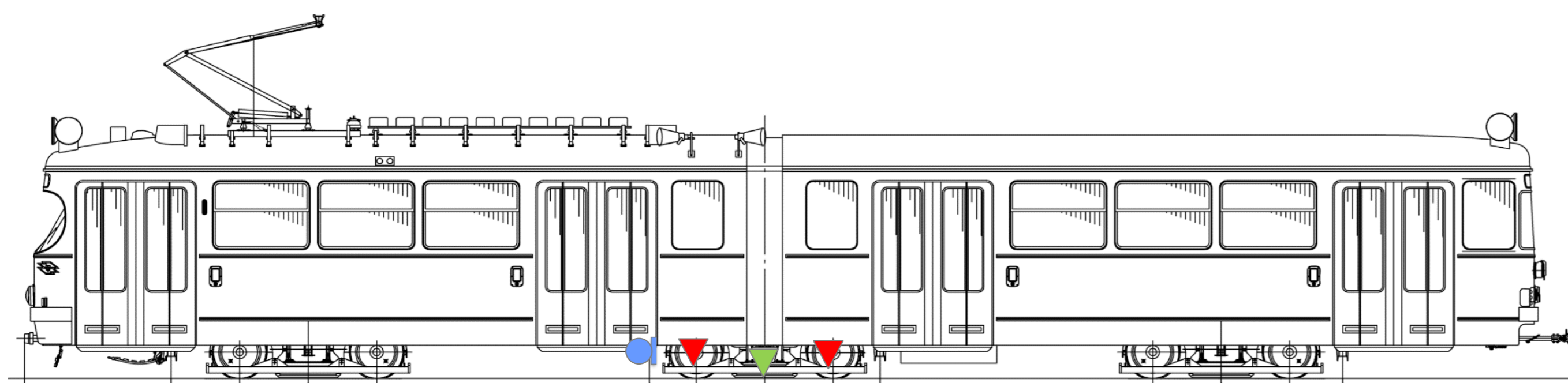
# DETECTING AND CLASSIFYING RAIL CORRUGATION BASED ON AXLE BEARING VIBRATION

## 1. BACKGROUND

### Track inspection using a designated vehicle

Vienna's tram network is regularly surveyed by an inspection tram which uses optical techniques to measure wear of the rail head and covers the entire network biannually.

In order to expand the vehicle's inspection capabilities, **axle bearing accelerometers** were combined with microphone data to monitor **vibro-acoustic onboard emissions**. That way, the dynamic interaction between the wheels and the rails can be monitored across the network.



## 2. MOTIVATION

### Automatic corrugation detection

One type of defect considered during routine inspection is corrugation, which is a periodic deformation (5-15 cm) of the rail head extending across tens of metres.

The presented study aims to expand upon existing studies, which have shown

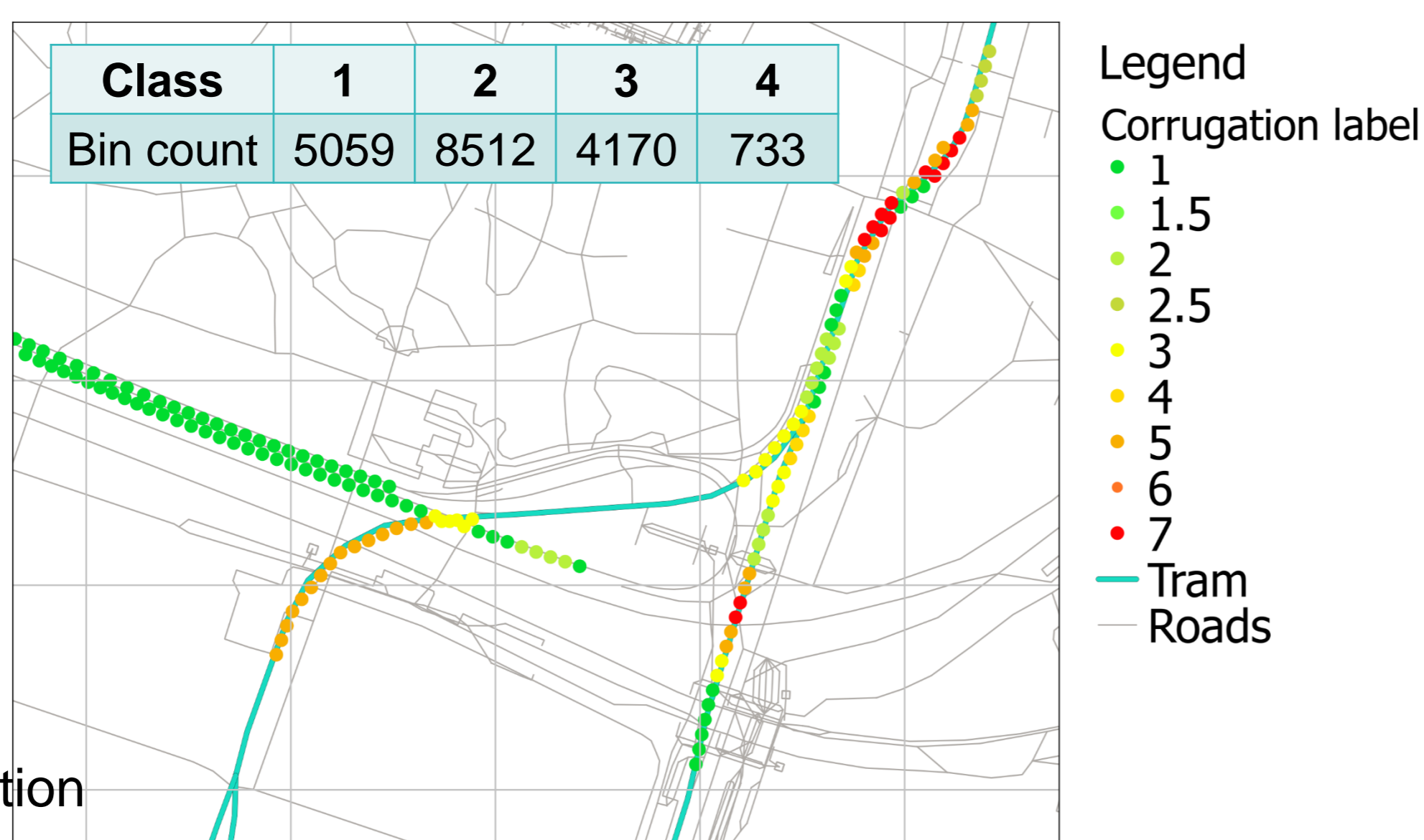
- the feasibility of estimating corrugation from axle box acceleration on heavy rail [1], and
- the application of machine learning algorithms to detect road surface conditions using onboard data [2].

## 4. LABELLED DATA

### On-site corrugation classification

The corrugation extent of around 9 km of track was determined by maintenance personnel during in-situ inspections

1 = no corrugation  
7 = very strong corrugation



### Supervised learning

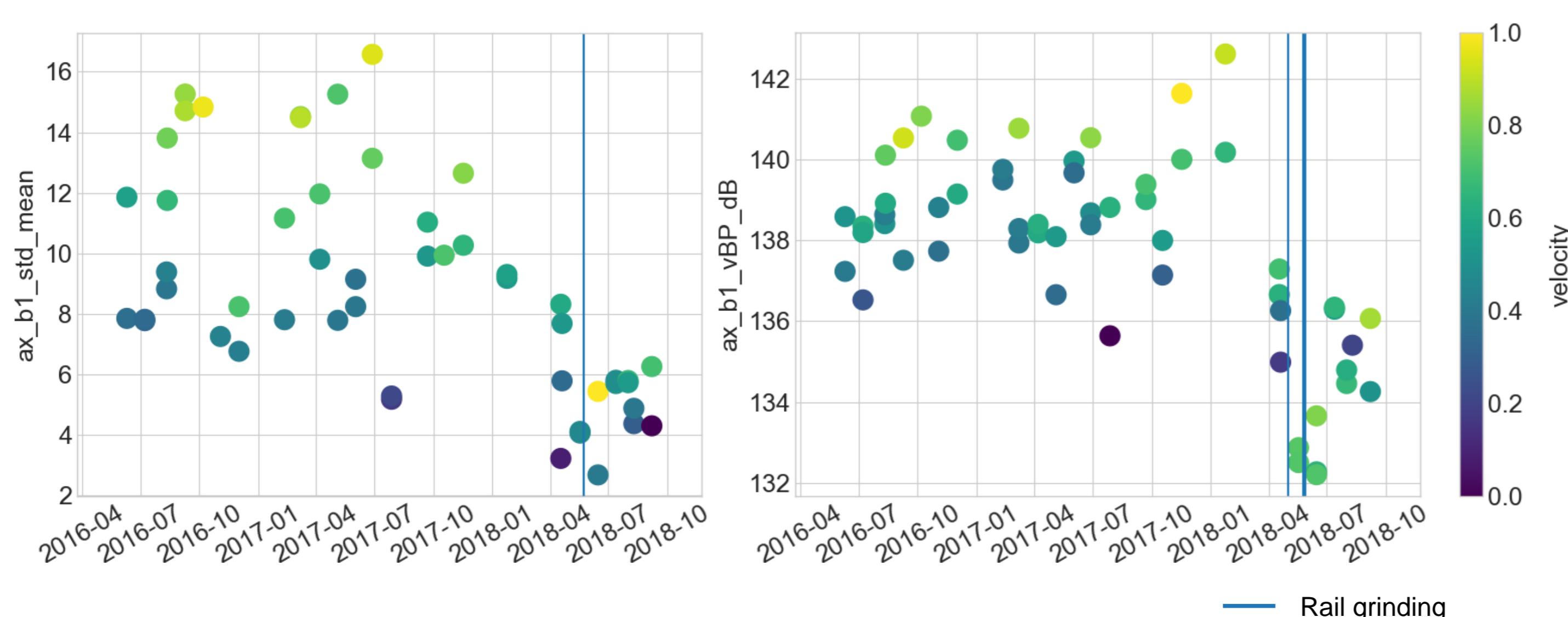
Data split: 70% training, 30% testing for standard classification methods:

- ➔ Logistic regression (LR)
- ➔ Random forests (RF)
- ➔ Support vector machines (SVM)
- ➔ Linear discriminant analysis (LDA)

Random stratification				
Classifier	LR	RF	SVM	LDA
Accuracy on test data	0.66	0.70	0.81	0.7
Optimal hyperparameters (optimised with 5-fold CV)	C: 1000 Penalty: L2	Bootstrap: False Max. depth: 30 Min. samples split: 3	C: 10	Components: 20 Solver: lsqr

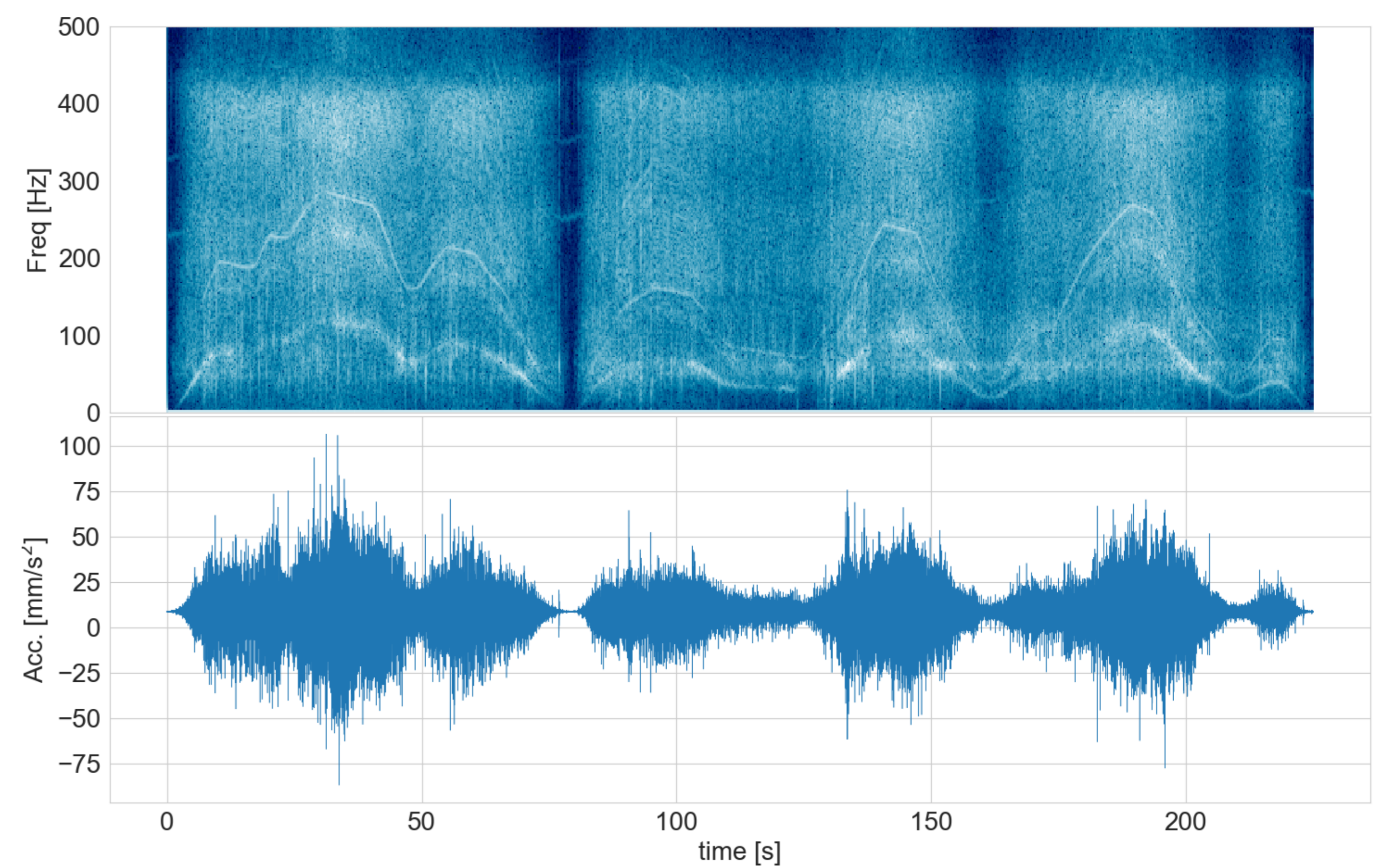
## 5. CLASSIFICATION

The trained classifiers were applied to all survey records. For bins with multiple passes over the last three years, a timeline of feature values became available and can be used in condition monitoring together with the classification result.



## REFERENCES

- [1] M. Bocciaone, A. Caprioli, A. Cigada, and A. Collina, "A measurement system for quick rail inspection and effective track maintenance strategy," *Mechanical Systems and Signal Processing*, vol. 21, no. 3, pp. 1242–1254, 2007.  
 [2] Christian Gorges, Kemal Öztürk, and Robert Liebich, "Impact detection using a machine learning approach and experimental road roughness classification," *Mechanical Systems and Signal Processing*, vol. 117, pp. 738–756, 2019.



## 3. VIBRATION FEATURES

Time domain data were split into **5 m bins**. This distance was chosen given the max. vehicle speed (50 km/h), the sampling rate (2 kHz) and the specifications of maintenance work.

- ➔ Standard deviation
- ➔  $L_{acc,F}$  (dB re.  $10^{-6}m/s^2$ )
- ➔  $L_{acc,F,vBP}$  (variable bandpass)
- ➔ Intensity ratio ( $L_{acc,F,vBP}/L_{acc,F}$ )
- ➔  $L_{acc,F,i}$  (3.15-315 Hz)
- ➔ Delta to expected value per bin
- ➔ Correlation to neighbouring bins

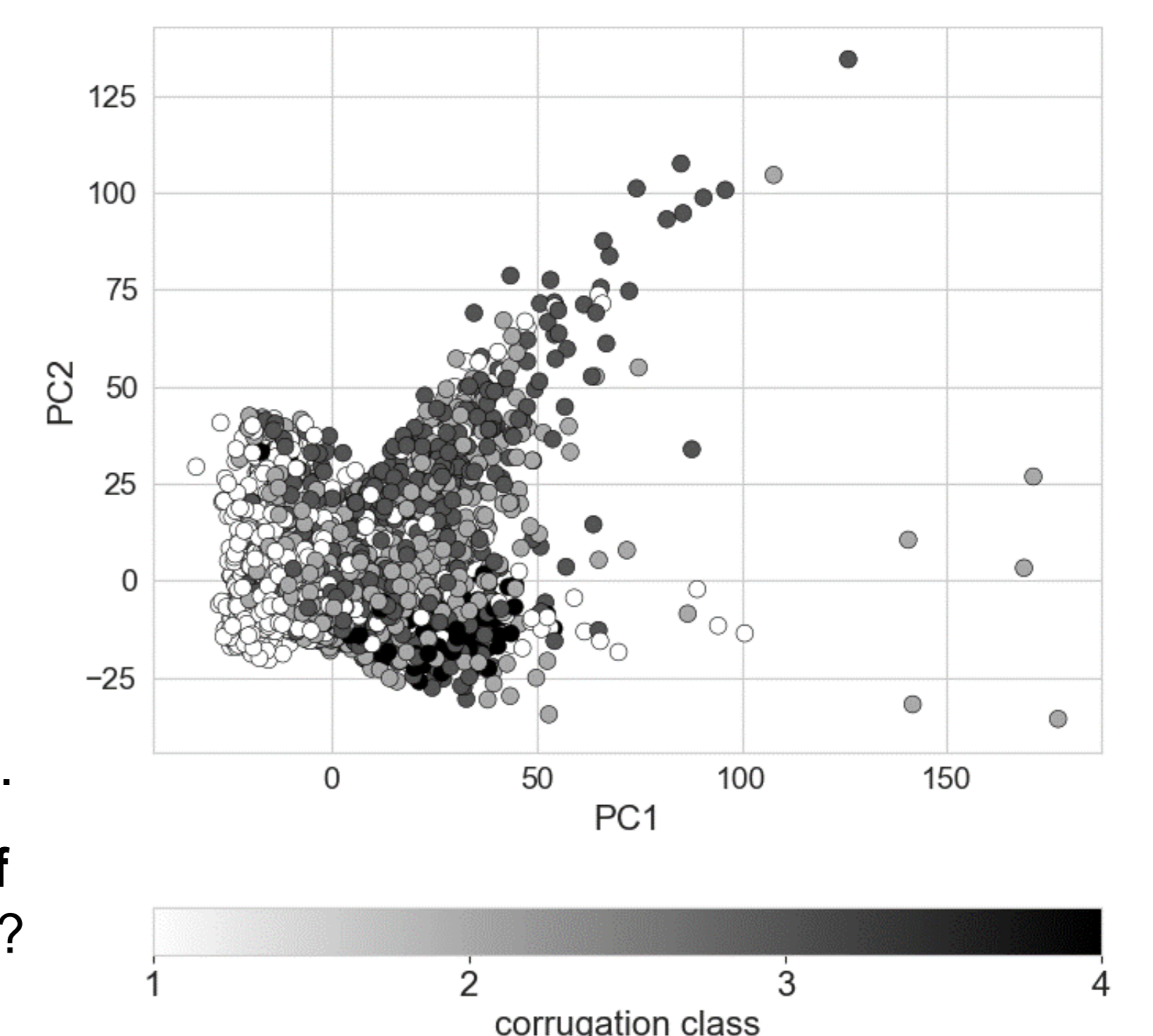
## Challenges

**Subjective classification** of corrugation and classes considered superfluous for maintenance decisions.

**Imbalanced dataset**, which potentially leads to overfitting in small classes.

**Independent neighbouring bins?** Track geometry and vehicle dynamics may be similar.

What is a reasonable **number of features** for this kind of problem?



## Solutions

Simplification prior to supervised learning: 4 classes in accordance with operator's maintenance procedures.

Oversampling techniques such as SMOTE, undersampling majority class.

Instead of random stratification, pick consecutive bins from different inspection sites.

Reduce features by excluding redundant sensors and using PCA.

Consider new features using ACF (lag of side peaks, periodicities)

## 6. WORK IN PROGRESS

Certain rail head irregularities lead to features which the algorithms may mistake for corrugation:

Switches, squats or rail breaks produce impulsive signals (high transient component) that can be differentiated from harmonic signals, but still yield high levels per bin.

### Alternative approaches

Microphone and vibration data were combined in a kernel regression (max. 5 features).

### Feature selection:

- ➔ 100 most reasonable features manually chosen and sent through a forward feature selection
- ➔ 12 features manually chosen and combinations of 5 tested brute force

### Best result using:

- ➔ Audio-ACF IQR of periodicity
- ➔ Audio-ACF zero crossings/metre
- ➔ Velocity
- ➔ Delta of acc. energy on bogie
- ➔ Delta of intensity ratio on bogie