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Characterising Monitoring Data from a Hunter Valley Rail Bridge

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Presentation Layout

Introduction

Literature Review / Research Background

Methodology

Results and Discussion

Conclusion and Recommendations



Figure 1: Ironbark Creek Bridge Mainline



Introduction – Background

Problem

- Rapid advances in sensing now enable continuous, high-resolution monitoring and large, long-duration SHM data sets.
- Data collection is no longer the main barrier; the key challenge is transforming complex sensor data into reliable engineering insights.

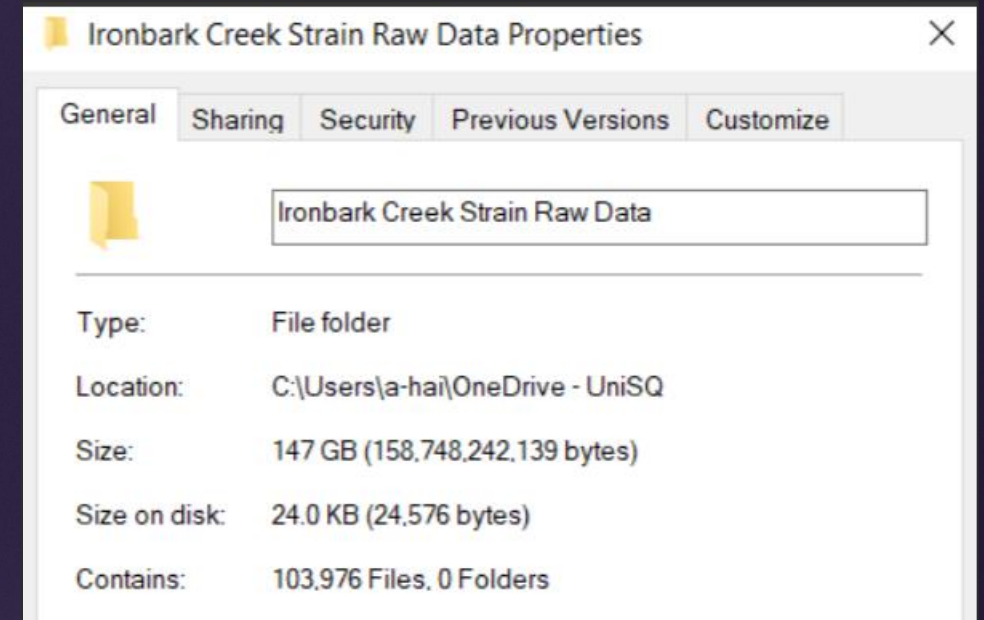


Figure 2: The study dataset reached 147 GB, enabling extensive experimentation



Introduction – Context

Context: Hunter Valley Freight Network

- Moves ~196.5 Mtpa of coal from 40 mines to the Port of Newcastle, forming a core part of the world's largest coal export chain.
- High axle loads and intense traffic frequency place significant fatigue demand on its rail bridges.
- Despite this importance, little published work examines long-term monitoring of Hunter Valley rail bridges.
- Provides an ideal natural laboratory for advancing data-driven SHM in heavy-haul environments.



Figure 3: The Hunter Valley Coal Chain – the worlds largest coal export network, yet lacks specialized rail bridge SHM research



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Introduction – Scope

Scope of Study: Ironbark Creek Bridge

- Single span heritage steel truss rail bridge
- Located in Hunter Valley, NSW
- 31 strain gauges instrumented by EngAnalysis
- 20-month continuous data set
- ~ 104,000 train events captured



Figure 4: Layout arrangement of strain gauges along Ironbark Creek Bridge



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Introduction – Objectives

Characterise long term strain gauge monitoring data from a Hunter Valley rail bridge to:

- Quantify fatigue damage and assess structural health of critical rail bridge members.
- Identify patterns and trends in monitoring data.
- Provide insights into structural health and performance over time.
- Support data-driven condition assessment and predictive maintenance for Hunter Valley rail bridges.



Literature Review/Research Background

Accuracy of strain gauge data

- Axle loads estimated from strain gauges within 2.5% of true weight (Pimentel et al. 2021)
- Strain histories resolved at $\sim 1 \mu\epsilon$ precision using wireless foil gauges (Bischoff et al. 2009)

Preprocessing of data

- Correct drift and temperature effects using thermal/offset compensation (Bischoff et al. 2009)
- Use low-pass filtering to remove high-frequency vibration and retain quasi-static response (Sun et al 2024)
- Remove non-physical spikes and faulty channels using outlier screening (Tibaduiza et al. 2013)

Quantification of fatigue damage

- Literature notes fatigue the most common failure mechanism of rail bridges
- Convert strain to stress ranges $\rightarrow$ apply rainflow counting $\rightarrow$ compare cycles to S–N curves $\rightarrow$ accumulate damage with Palmgren–Miner Rule (Lund et al. 2004, Saberi et al. 2016, and Leander et al. 2010)



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Literature Review/Research Background

Unsupervised ML in data-driven SHM

- PCA compresses correlated event-level strain features into a low-dimensional behavioural space, reducing redundancy while preserving dominant response patterns (Azim et al. 2021)
- k-means clustering groups train passages by similarity to distinguish different operational regimes (Díez et al. 2016, Armijo et al. 2024)

Characterisation of clusters

- Performed by reprojecting results into the original feature space and examining operational drivers
- Axle count, axle mass, and speed plotted against fatigue damage to determine trends/patterns (Sadeghi et al. 2022)



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Methodology – Tools & Technologies

Strain gauges

- Captures strain response from train loading

MATLAB

- Process and analyse data, run simulations

DGX System

- Super-computer for rapid large-scale computations

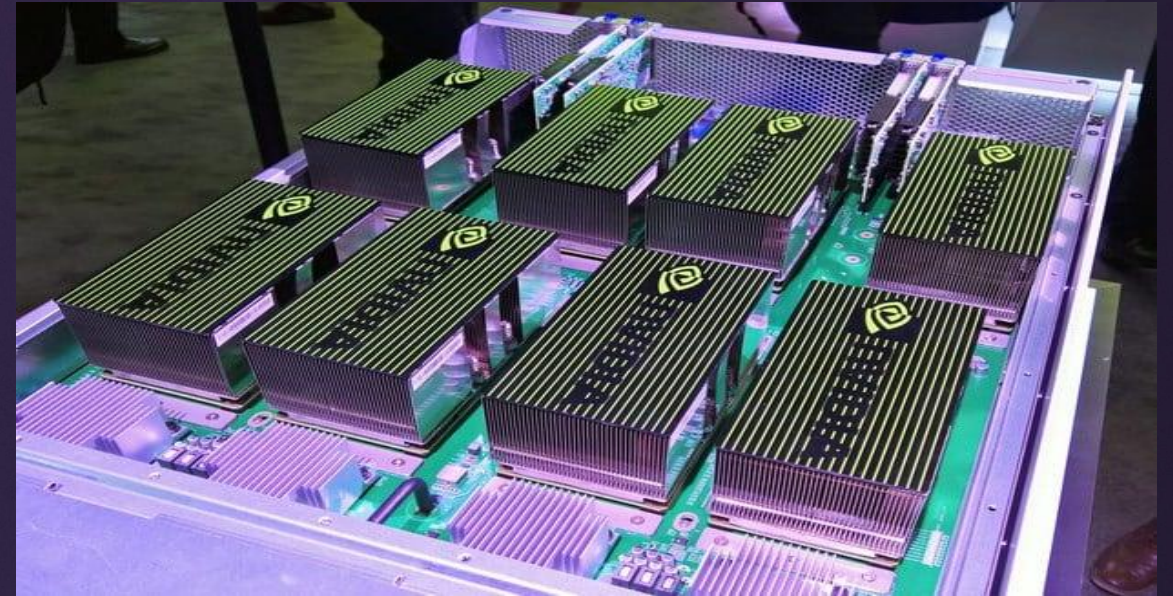


Figure 5: NVIDIA DGX System



Methodology – Design Process

Methodology can be separated into 3 phases:

1. Data collation/processing

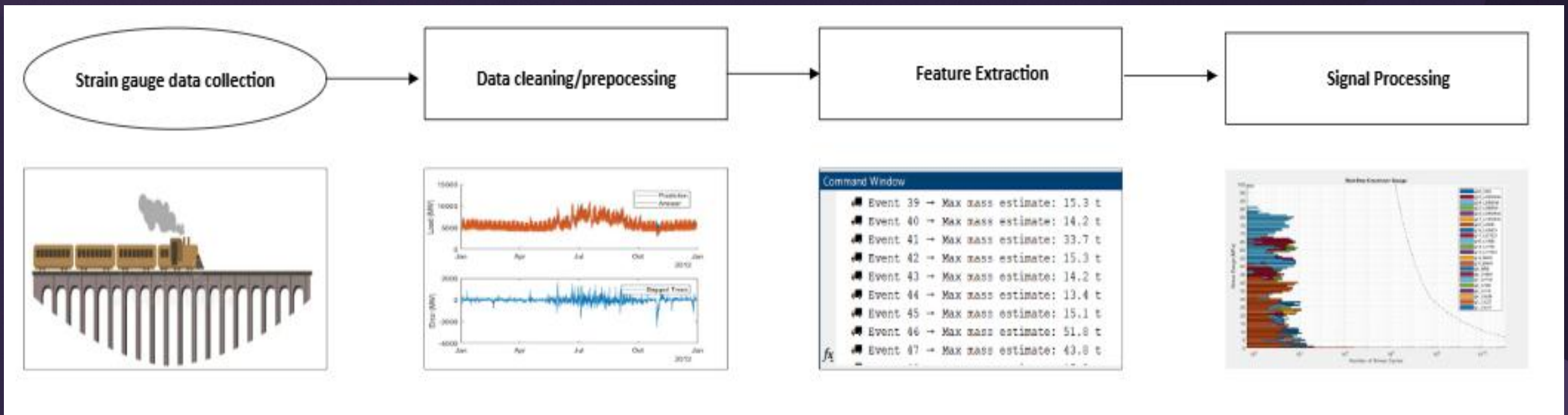


Figure 6: Phase 1 of Methodology



Methodology – Design Process

2. Unsupervised Machine Learning (ML) for pattern discovery

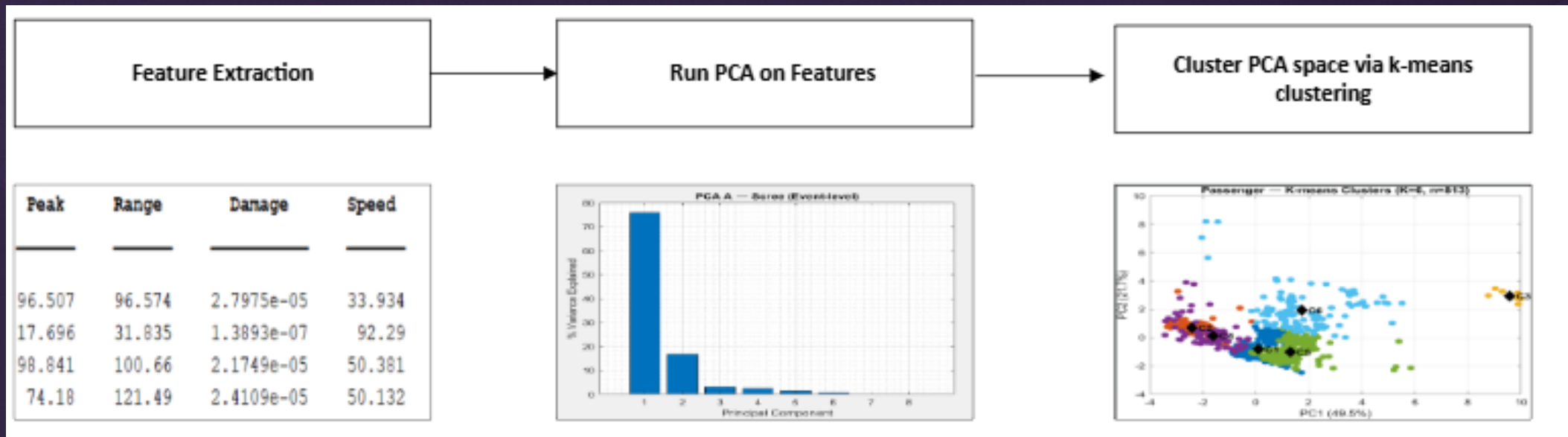


Figure 7: Phase 2 of Methodology



Methodology – Design Process

3. Characterisation of Monitoring Data

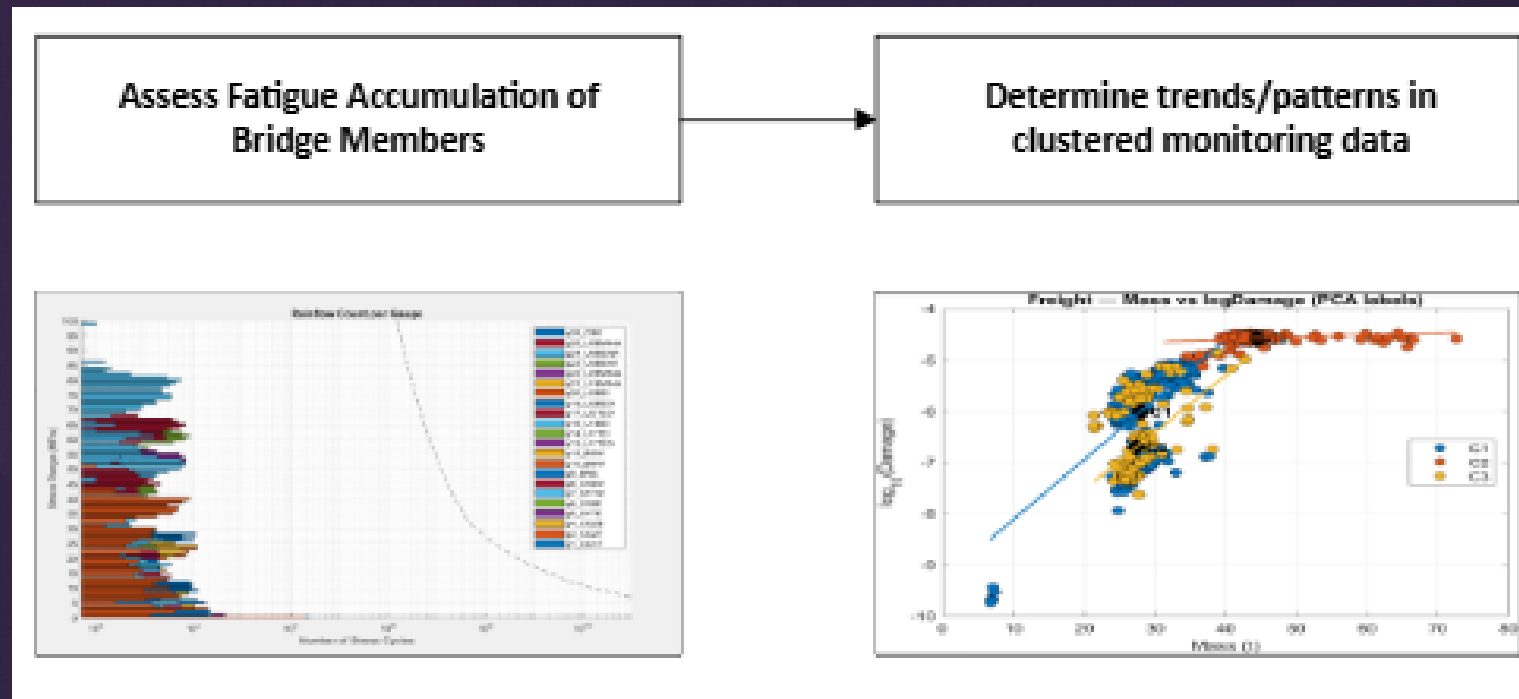


Figure 8: Phase 3 of Methodology



Methodology – Data Collation/ Processing

Strain gauge data collation

- Collected by industry partner EngAnalysis (Newcastle, NSW)
- 22 strain gauges installed across Ironbark Creek Rail bridge
- Monitoring window: 20 months (Apr 2022 – Dec 2023)
- Dataset size $\approx 104,000$ events captured

Gauge Number	Channel ID	Description
1	g1_cg1t	Cross-Girder 1 Top
2	g2_cg1b	Cross-Girder 1 Bottom
3	g3_cg2t	Cross-Girder 2 Top
4	g4_cg2b	Cross-Girder 2 Bottom
5	g5_s1te	Stringer 1 Top East
6	g6_s1be	Stringer 1 Bottom East
7	g7_s1tw	Stringer 1 Top West
8	g8_s1bw	Stringer 1 Bottom West
9	g9_bne	Diagonal Brace North East
10	g10_bnw	Diagonal Brace North West
11	g11_bse	Diagonal Brace South East
12	g12_bsw	Diagonal Brace South West
13	g13_u1teo	Upright 1 Top East Outer
14	g14_u1tei	Upright 1 Top East Inner
15	g15_u1beo	Upright 1 Bottom East Outer
16	g16_u1bei	Upright 1 Bottom East Inner
17	g17_u2teo	Upright 2 Top East Outer
18	g18_u2tei	Upright 2 Top East Inner
19	g19_u2beo	Upright 2 Bottom East Outer
20	g20_u2bei	Upright 2 Bottom East Inner
21	g21_u1bwna	Upright 1 Bottom West Neutral Axis
22	g22_u2bwna	Upright 2 Bottom West Neutral Axis

Figure 9: Location of gauges installed along Ironbark Creek Rail Bridge



Methodology – Data Collation/ Processing

Data cleaning (Pre-processing)

- Clean signals (remove drift, low-pass filter, re-baseline)
- Drop unrealistic spikes.
- Keep only sensible results (e.g., implausible speeds/masses removed)

Feature extraction

- Speed, axle mass, vehicle type (freight/passenger/locomotive), peak stress, and axle numbers estimated via engineering and mathematical relationships

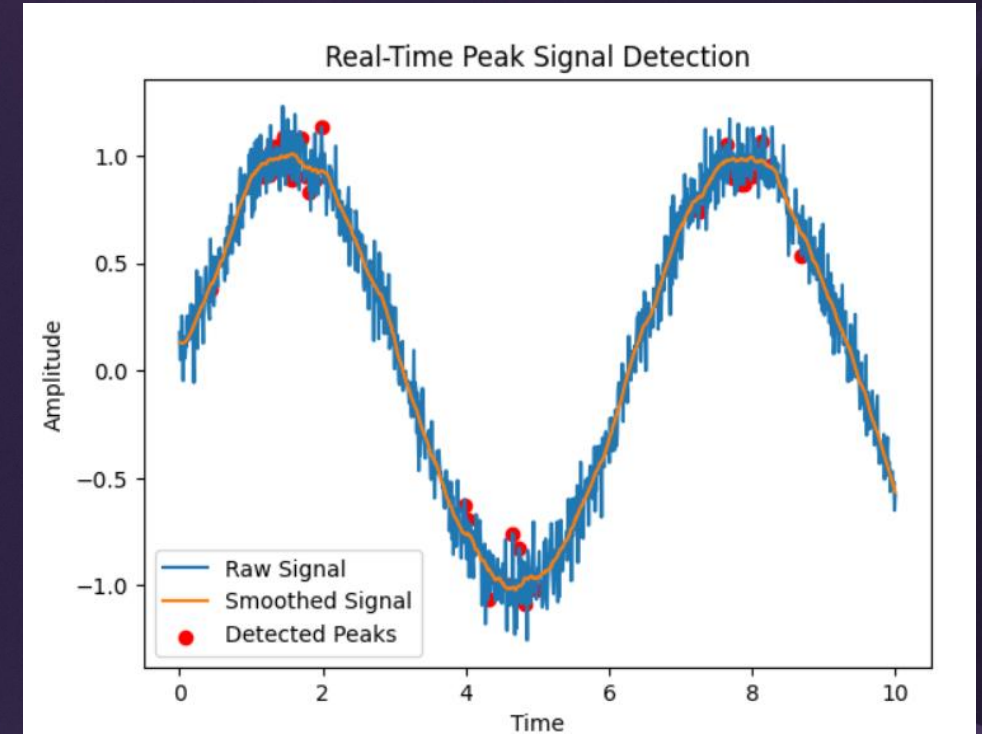


Figure 10: Smoothed strain (orange) enables reliable peak extraction (red) from noisy raw (blue)



Methodology – Data Collation/ Processing

Fatigue quantification

- Extract peaks and valleys to define stress cycles
- Use rainflow counting to bin cycles by stress range
- Apply Miner's Rule to compute total fatigue damage for the study period

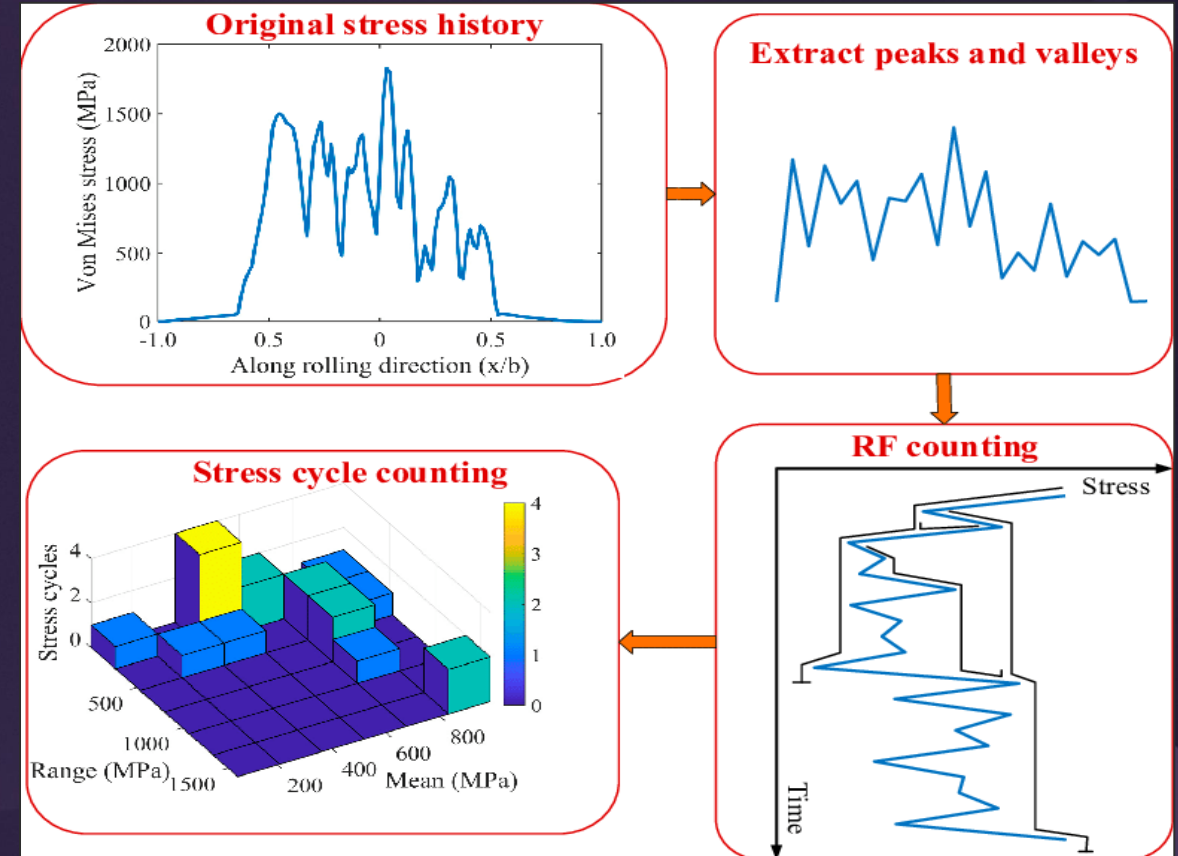


Figure 11: Flow chart of the Rainflow Cycle Count Process



Methodology – Machine Learning

Run PCA on extracted features

- Features are z-scored to put all values on standardized scale
- Build a matrix with one row per event for all features and enter all z-scores
- Use *MATLAB Statistics & Machine Learning Toolbox* to run PCA on the matrix
- Visualize the two most informative components in a scatter plot to explore patterns and relationships in data

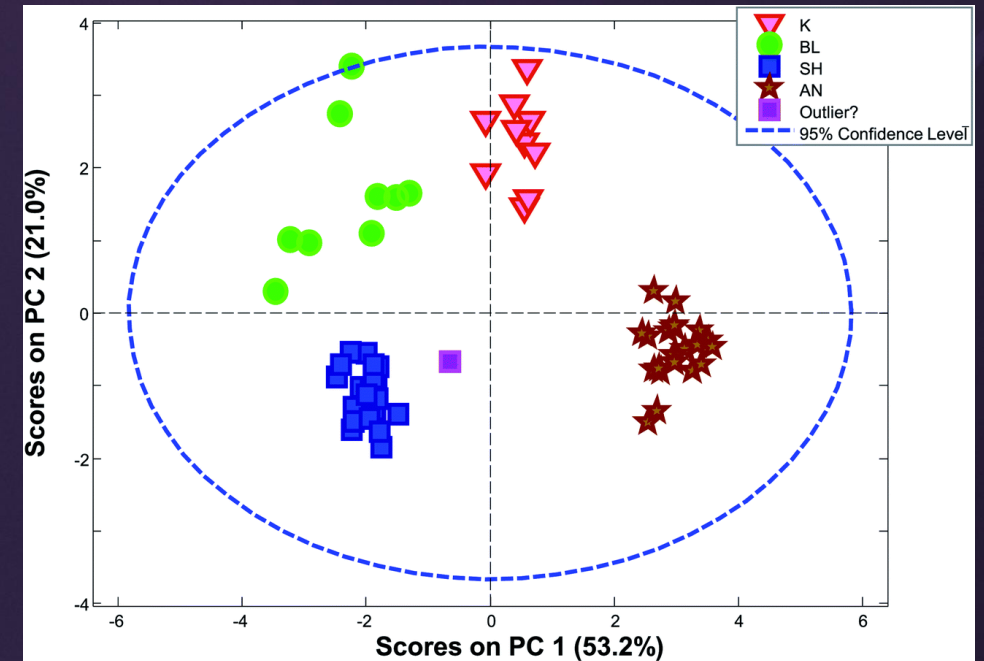


Figure 12: Example of PCA plot showing how data points group by similarity in the first two principal components



Methodology – Machine Learning

Run k-means clustering on retained PC groups

- Use *MATLAB Statistics & Machine Learning Toolbox* to run k-means clustering on PCA space
- Using calculated silhouette scores, similar events are clustered together

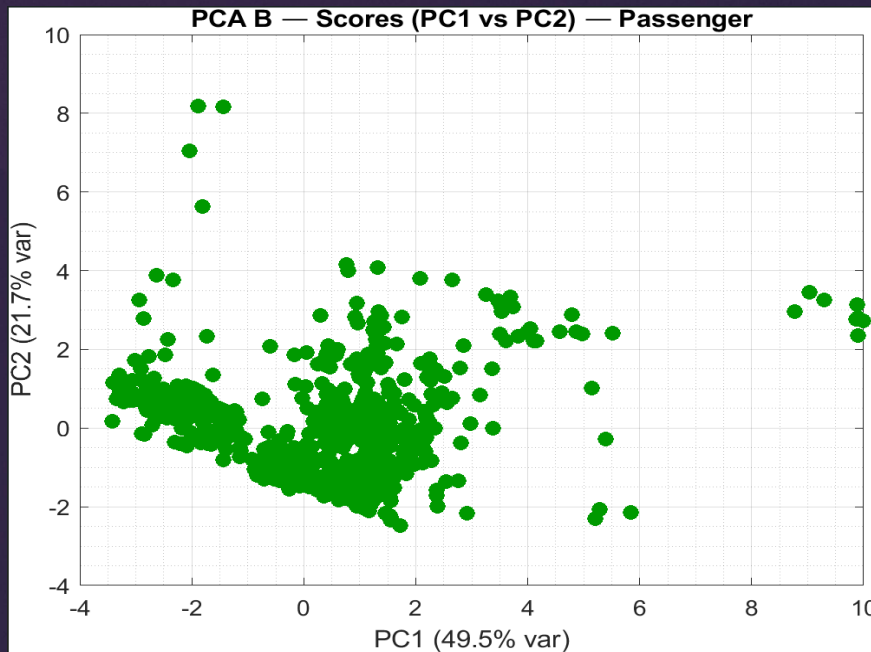


Figure 13: PCA space for passenger vehicles (before k-means clustering)

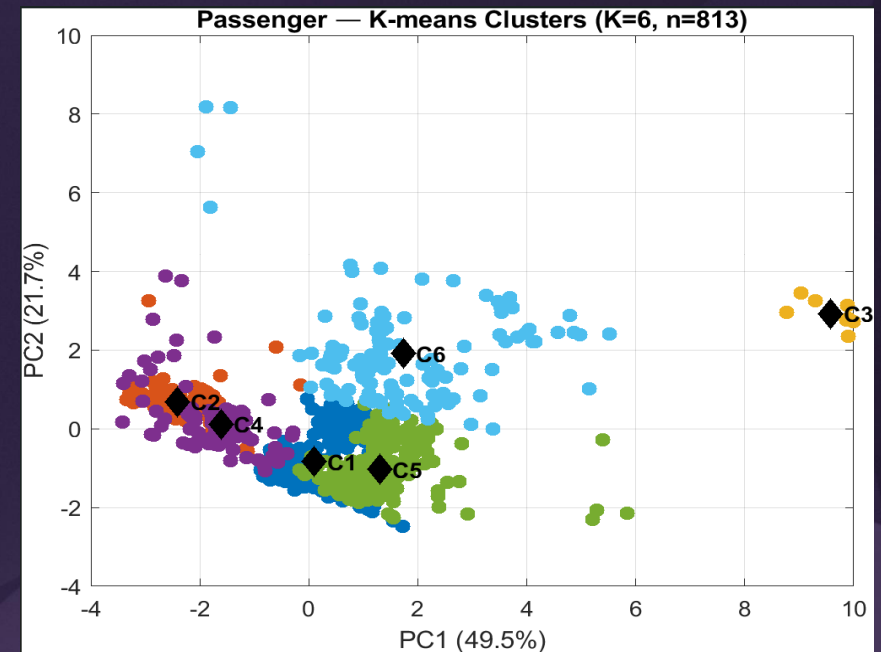
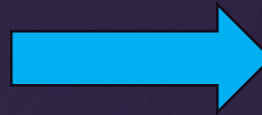


Figure 14: PCA space post clustering



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Methodology – Characterising Monitoring Data

Reprojecting PCA clusters to original features to determine patterns/trends

- Axle mass vs fatigue damage
- # of axles vs fatigue damage
- Speed vs fatigue damage

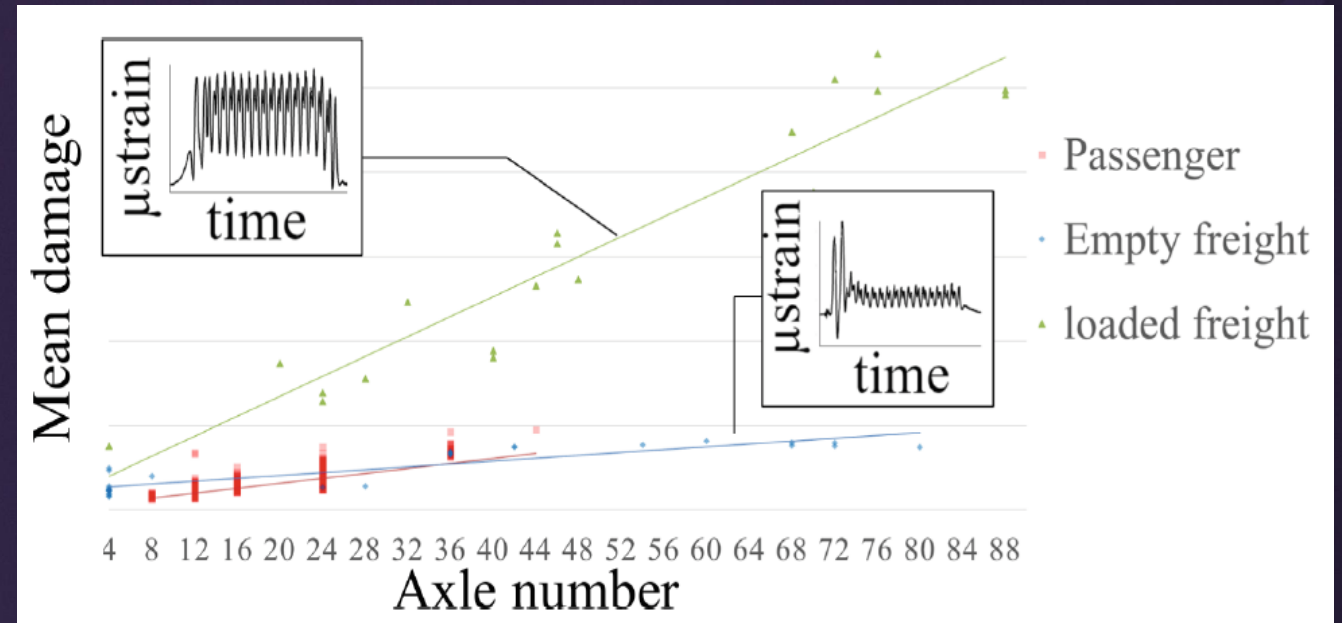


Figure 15: Sadeghi et al. 2022 visualized axle number against mean damage to find linear relationship



Results and discussion

PCA successful in reducing variability & grouping data outputs by similarity

- Plotting PC1 vs PC2 reduces variable dataset into 2D space which still captured ~ 83% of dataset variance
- Closely replicates Azim et al. 2020 results
- Visualising PCA results shows natural groupings emerging

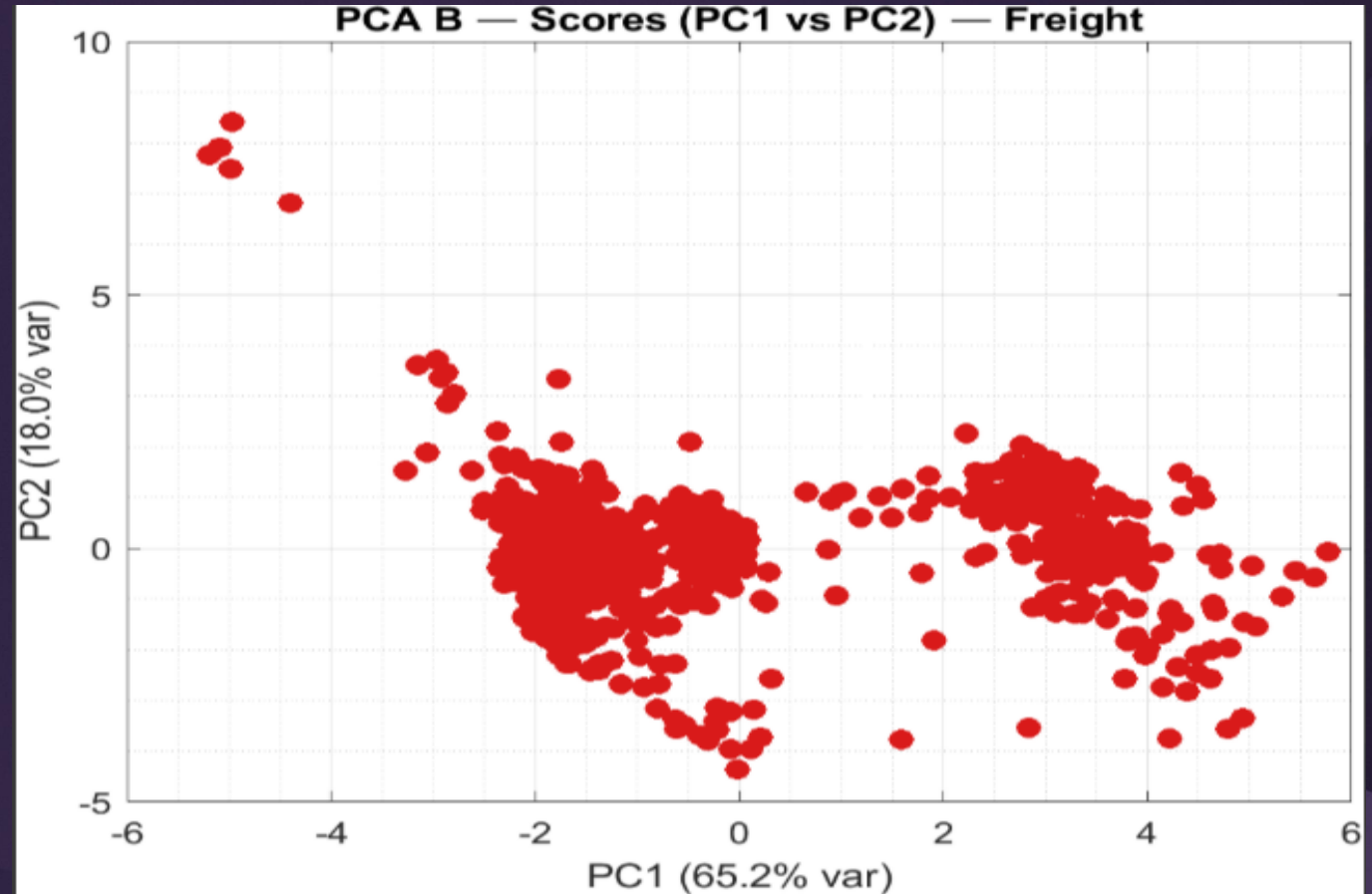


Figure 16: PC1 vs PC2 for freight data in PCA space



Results and discussion

K-means clustering successful in capturing different operational regimes

- This helped to analyse unique operational regimes independently, reducing the initial non-monotonic nature of the data set
- Clustering metrics in agreement with Gui et al. 2024

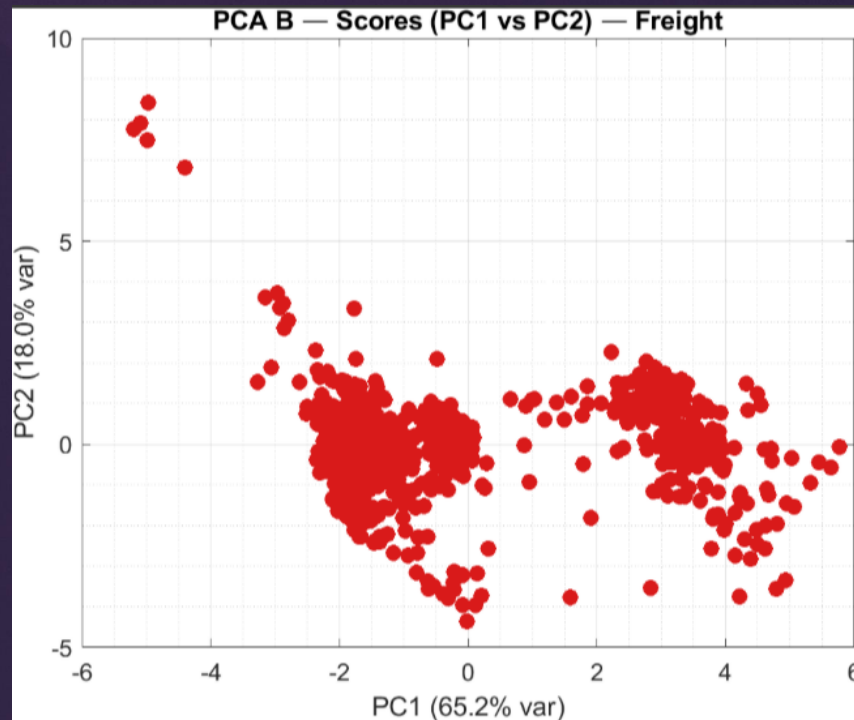


Figure 17: PCA freight data pre clustering

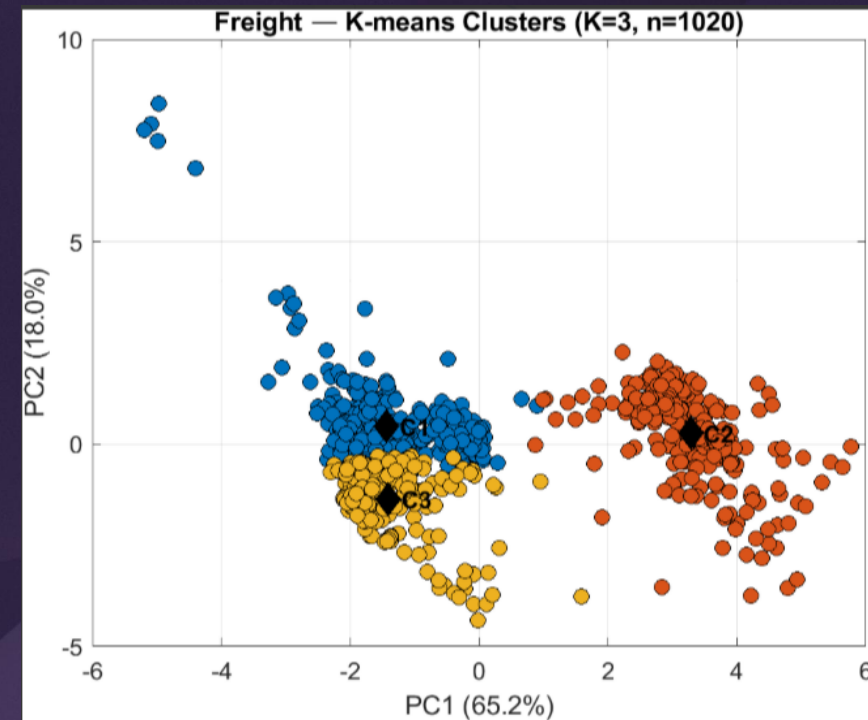
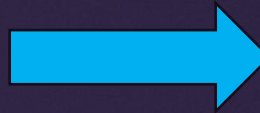


Figure 18: PCA freight data post clustering



Results and discussion

Axle count is a main driver of rail bridge fatigue damage

- Past threshold of ~ 90 peaks, fatigue damage linearly increases
- In agreement with findings from Sadeghi et al. 2022

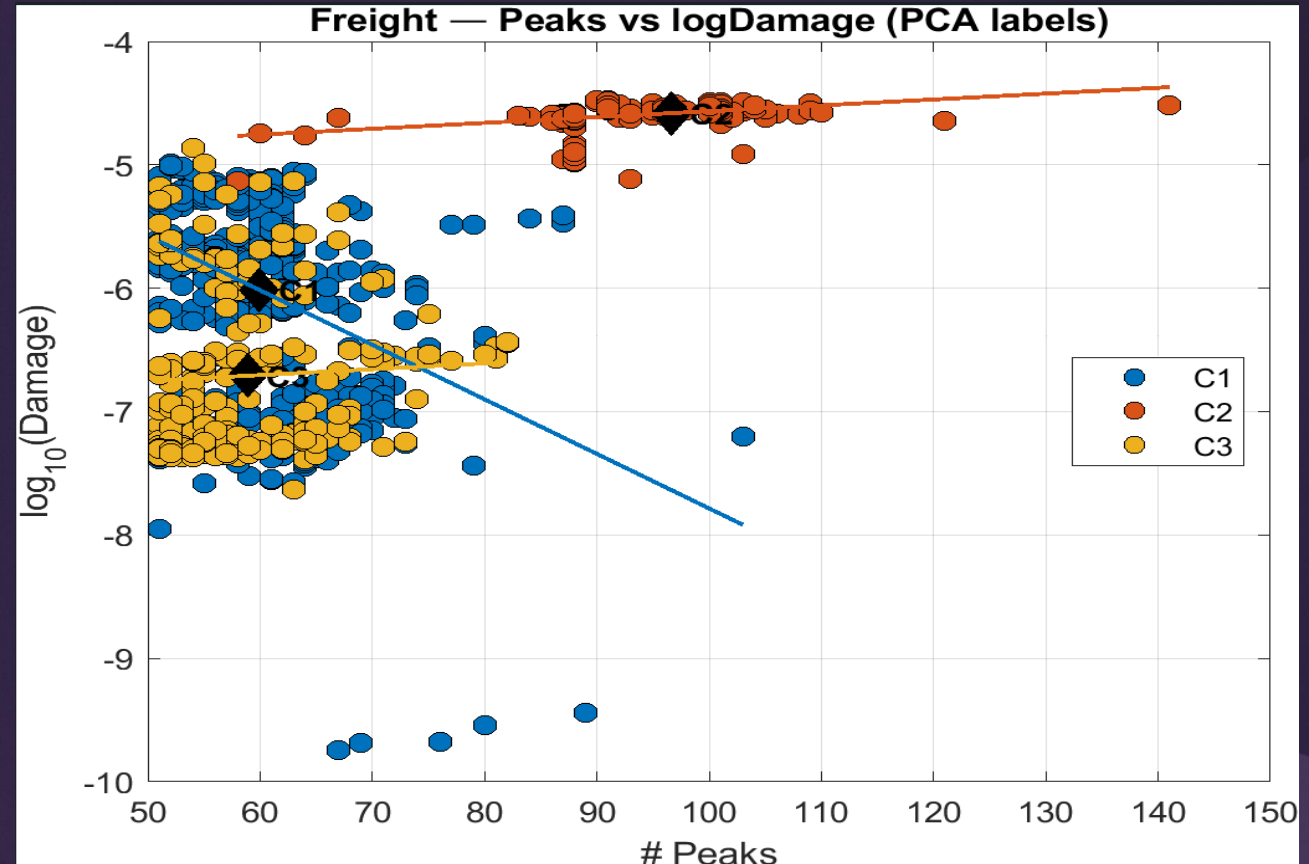


Figure 19: Axle peaks vs Fatigue damage (per cluster)



Results and discussion

Axle mass is another main driver of rail bridge fatigue damage

- Damage increases rapidly until threshold of $\sim 40\text{t}$ axle mass, more steadily in heavier cluster
- In agreement with findings from Sadeghi et al. 2022

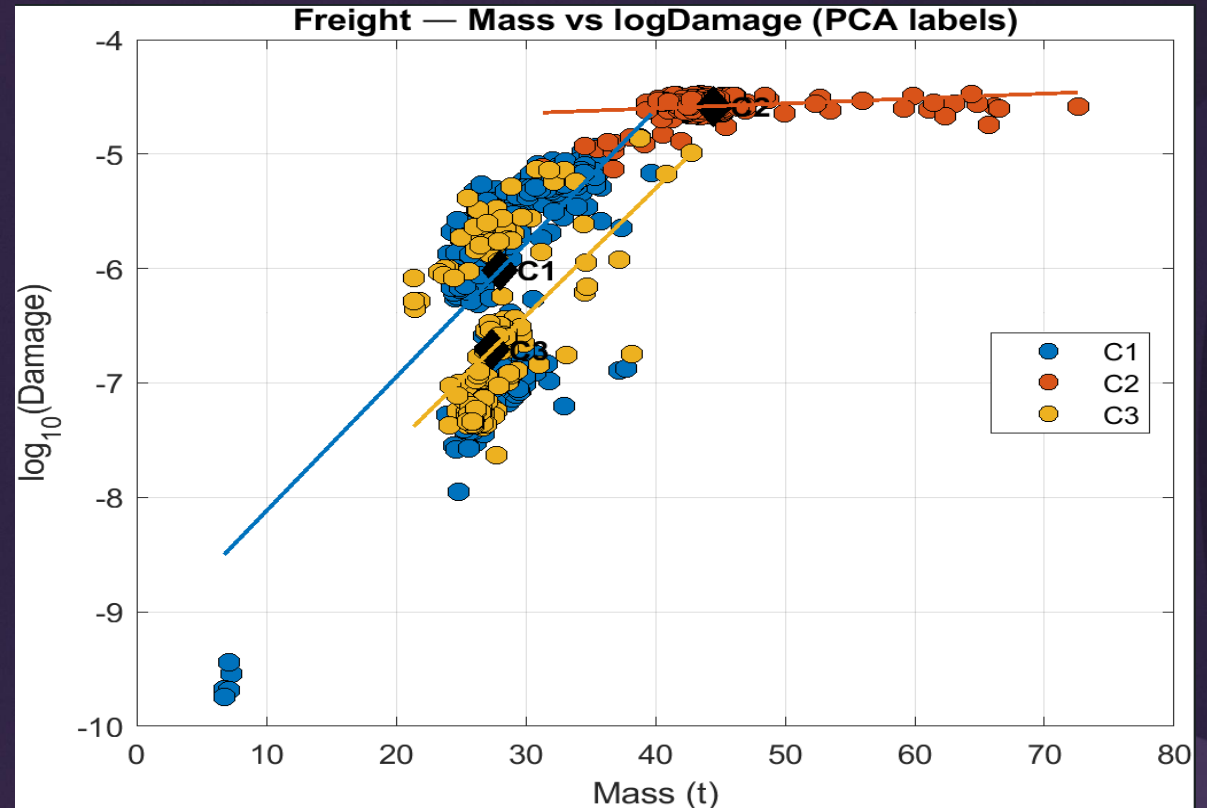


Figure 20: Axle mass vs Fatigue damage (per cluster)



Results and discussion

Speed has no clear influence on damage for freights

- Heavier freights generate consistently high stresses regardless of speed
- Lighter freights show a negative speed–damage relationship
- In disagreement with findings from Sadeghi et al. 2022

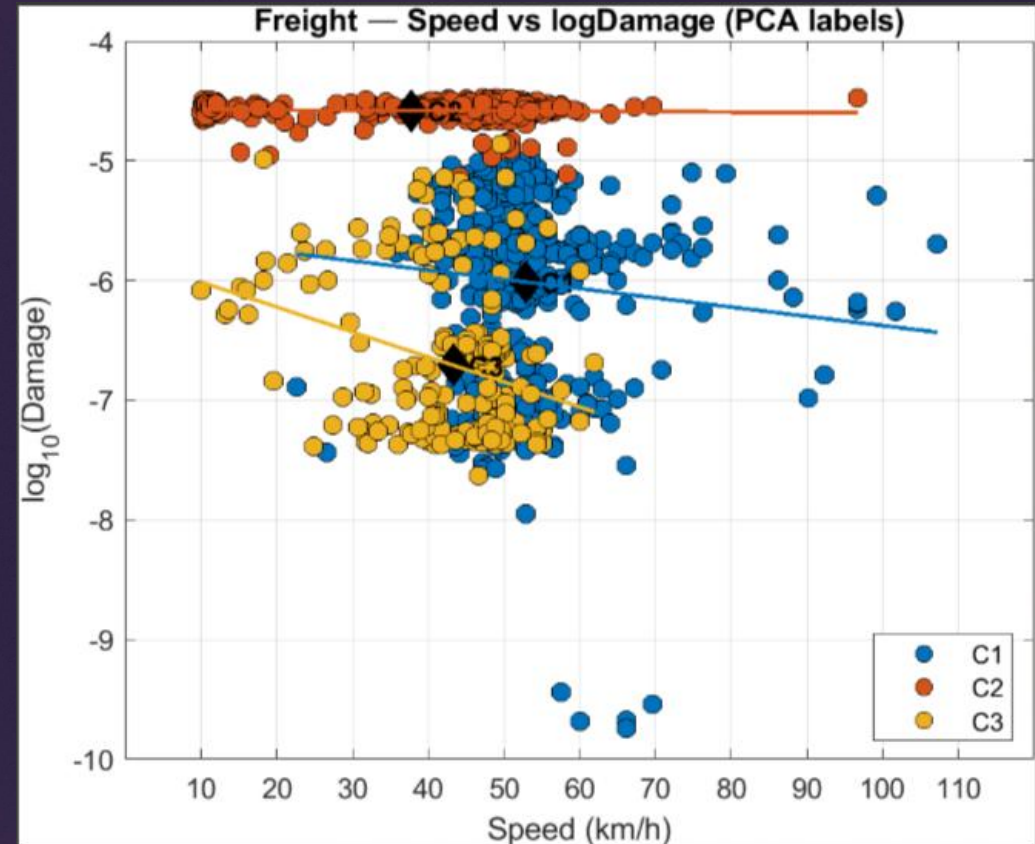


Figure 21: Speed vs Fatigue damage (per cluster)



Results and discussion

Certain bridge members accumulating markedly higher fatigue damage than others

- Uprights g13 and g16 estimated to have critical remaining fatigue life of 30 and 10 years respectively
- Uprights and their gusset-plate connections identified in literature as fatigue critical locations of railway truss bridges (Teixeira et al. 2024)

Gauge	Damage per event avg	Damage rate per day	Years_to_D1
g1_CG1T	1.57E-08	1.48E-06	1849.4
g3_CG2T	5.91E-09	5.57E-07	4919.9
g4_CG2B	6.40E-09	6.03E-07	4543.5
g5_S1TE	1.84E-07	1.73E-05	158.1
g6_S1BE	2.90E-07	2.74E-05	100.11
g7_S1TW	1.70E-07	1.60E-05	171.02
g8_S1BW	3.06E-07	2.88E-05	95.028
g9_BNE	3.16E-09	2.98E-07	9184.6
g10_BNW	2.06E-09	1.94E-07	14098
g12_BSW	1.52E-09	1.43E-07	19101
g13_U1TEO	9.42E-07	8.88E-05	30.852
g14_U1T1E	1.48E-07	1.39E-05	196.57
g16_U1BE1	2.83E-06	2.67E-04	10.251
g17_U2TEO	3.18E-08	3.00E-06	912.74
g19_U2BEO	1.05E-08	9.85E-07	2780.6
g20_U2BE1	3.58E-07	3.38E-05	81.135
g21_U1BWNA	3.93E-08	3.71E-06	739.34
g22_U2BWNA	4.23E-09	3.99E-07	6864.2
g23_U5BEN1	2.68E-08	2.53E-06	1084.7
g24_U6BENA	3.05E-07	2.89E-05	95.361
g25_U5BWNA	4.14E-09	3.91E-07	7012.8
g28_CBE	1.80E-09	1.70E-07	16110

Figure 22: Remaining fatigue life of Ironbark Creek Bridge gauged members



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Results and discussion

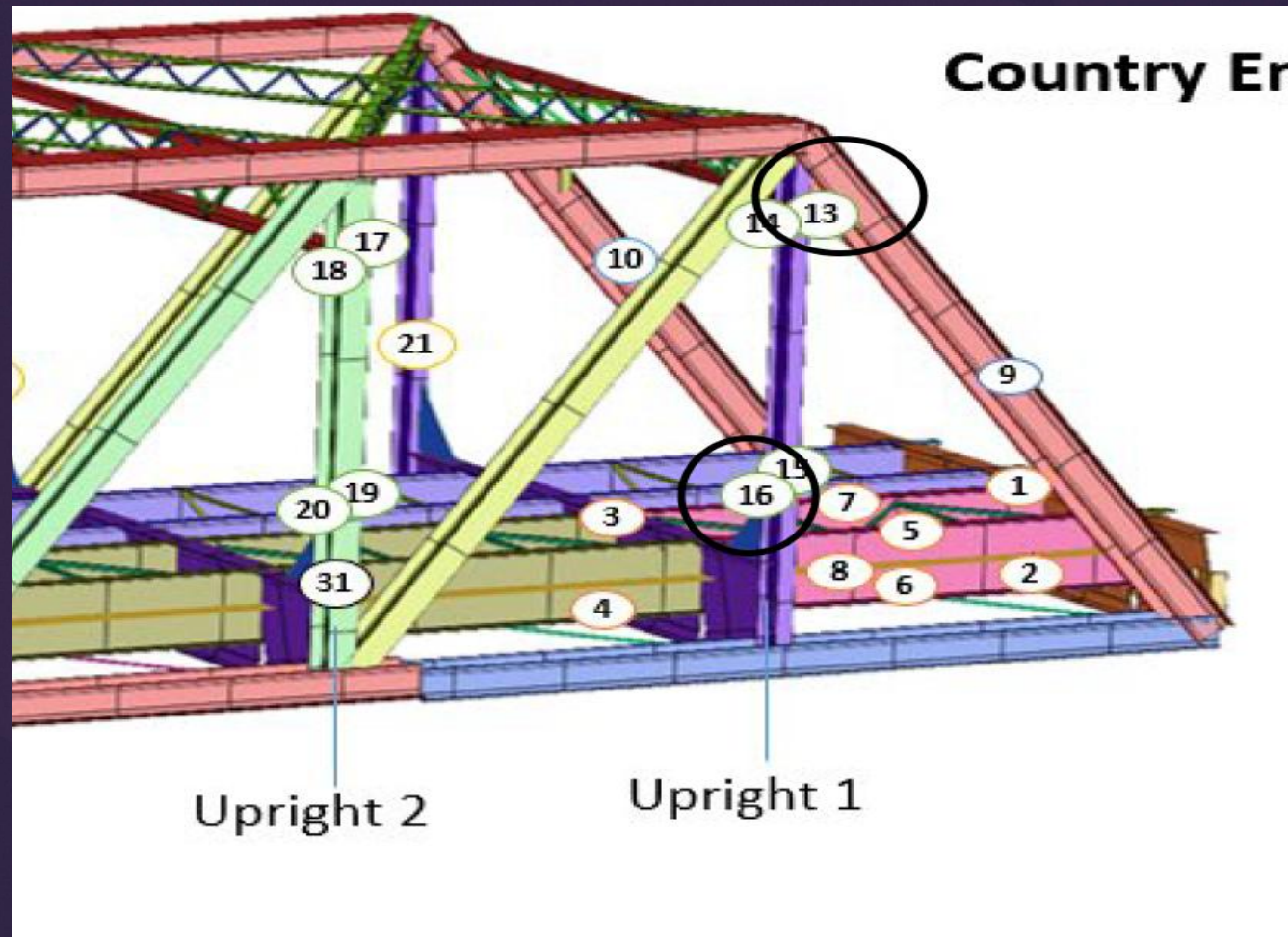


Figure 23: Localised uprights with critical fatigue life



Main findings and thoughts

Summary of findings

- Fully data-driven SHM revealed actionable rail bridge asset insights
- PCA filtered out low-information directions, reducing variability in datasets
- K-means grouped similar operational regimes, exposing patterns and trends
- Axle count and axle mass were the dominant drivers of fatigue damage
- Speed had no clear effect on freight vehicles
- Localised uprights were accumulating damage at markedly faster rates than other members along the bridge



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Main findings and thoughts

Potential real-world applications of study

- Demonstrate how data-driven SHM complements traditional inspections, direct load testing, and physics-based models.
- Methodologies developed in this study can be scaled and applied to mainline bridges across the Hunter Valley Coal Chain



Figure 24: The Hunter Valley Coal Chain – the worlds largest coal export network, yet lacks specialized rail bridge SHM research

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