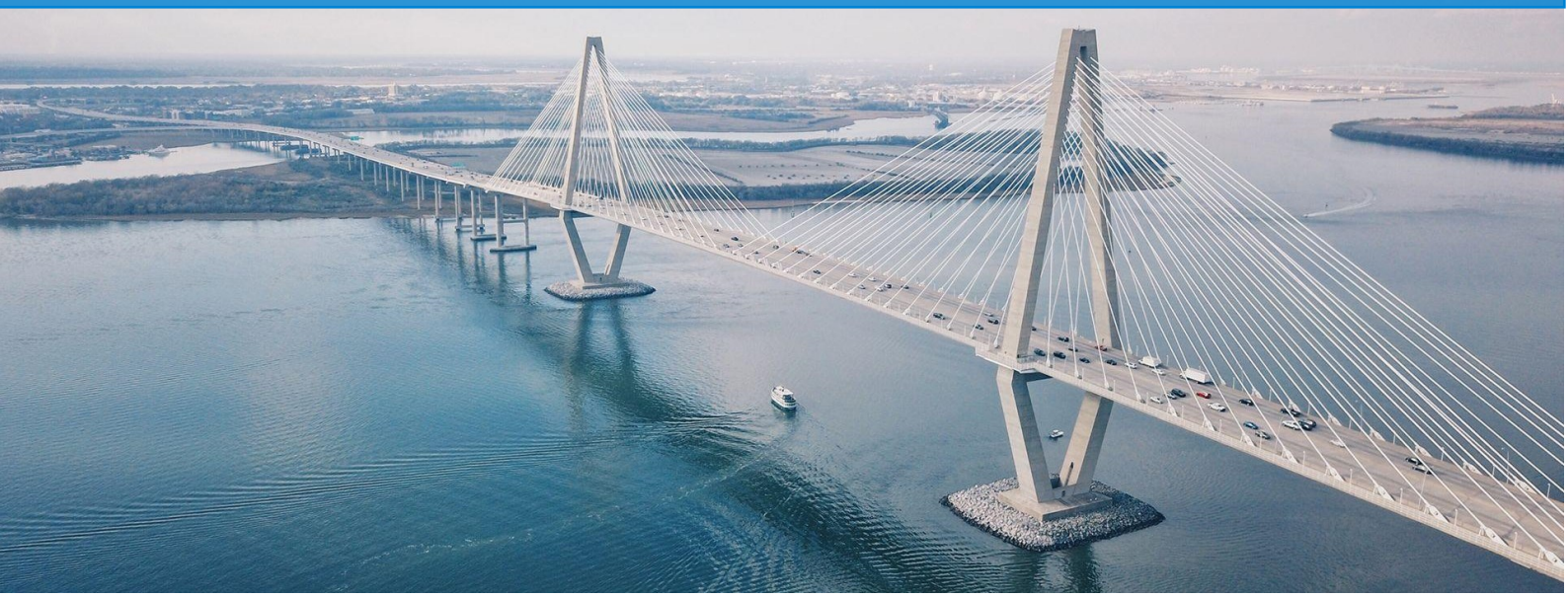
Territorial risks

SIRMA

STRENGTHENING INFRASTRUCTURE RISK MANAGEMENT IN THE ATLANTIC AREA



A Numerical & Experimental Repository

December 2023 (V1.0)

PUBLIC

SIRMA

STRENGTHENING THE TERRITORY'S RESILIENCE TO RISKS OF NATURAL, CLIMATE AND HUMAN ORIGIN

Application Code: EAPA_826/2018

A Numerical & Experimental Repository

WP 5 WP Title Instrumenting Transportation Infrastructures for Extreme Natural Hazards

Deliverable ID	**D5.2**
Deliverable name	**Numerical and Experimental Repository: WP5**
Lead partner	**University College Dublin (UCD)**
Contributors	UCD, Irish Rail (Partners) and collaborations from Trinity College Dublin, Ireland Indian Institute of Technology Guwahati, India

PUBLIC

SIRMA Project Synopsis

SIRMA aims to develop, validate and implement a robust framework for the efficient management and mitigation of natural hazards in terrestrial transportation modes at the Atlantic Area, which consider both road and railway infrastructure networks (multi-modal). SIRMA leads to significantly improved resilience of transportation infrastructures by developing a holistic toolset with transversal application to anticipate and mitigate the effects of extreme natural events and strong corrosion processes, including climate change-related impacts. These tools will be deployed for critical hazards that are affecting the main Atlantic corridors that is largely covered by SIRMA consortium presence and knowledge. SIRMA's objectives will address and strengthen the resilience of transportation infrastructures by:

- Developing a systematic methodology for risk-based prevention and management (procedures for inspection, diagnosis and assessment);
- Implementing a decision-making algorithm for a better risk management;
- Creating a hierarchical database (inventory data, performance predictive models, condition state indicators and decision-making tools), where information can be exchangeable between entities and across regions/countries;
- Developing a real-time process for monitoring the condition state of transportation infrastructure;
- Enhancing the interoperability of information systems in the Atlantic Area, by taking account of data normalization and specificity of each country.

SIRMA
STRENGTHENING INFRASTRUCTURE RISK MANAGEMENT IN THE ATLANTIC AREA

Interreg Atlantic Area
European Regional Development Fund

EUROPEAN UNION

Document Information

Document Name	Numerical and Experimental Repository: WP5	
Version No.	V1.0	
Due date	31/12/2022	
Report date	30/12/2022	
Number of pages		
Lead Author	Vikram Pakrashi (UCD)	
Other Authors	Eugene OBrien, UCD Cathal Bowe, Irish Rail Paul Mucchielli, UCD Basuraj Bhowmik, UCD Rohit Chawla, UCD Claire McGwoen, UCD	Tadhg Buckley, UCD E. Alexandra Micu, UCD Nurtaj Hossain, UCD Bidisha Ghosh, Trinity College Dublin (Collaborator) Budhaditya Hazra (Indian Institute of Technology Guwahati, Collaborator)
Dissemination level	Public	

Document History

Ver.	Date	Description	Authors	Checked by
0.1	16/07/2020	Creation of the document	Vikram Pakrashi, UCD	Belen Riveiro,UVigo
0.2	31/12/2022	Completion of first draft	Vikram Pakrashi, UCD	Eugene OBrien
0.3	07/01/2023	Completion of second draft	Vikram Pakrashi, UCD	Eugene OBrien

Document Approval

Ver.	Name	Position in project	Beneficiary	Date	Visa
1.0	Vikram Pakrashi	Partner		06/01/2023	

Executive Summary

This report presents a numerical and experimental repository created in the context of SIRMA. This report should also be read in conjunction with D5.2 report. The report first presents the development of real-time to near real-time detection of features of interest. Subsequently, the report addresses time. frequency and statistical markers for features of interest. Finally, machine learning, artificial intelligence and similar aspects around features of interest are investigated in terms of performance and comparison. The report distinguishes numerical and experimental aspects and finally demonstrates implementation in Irish sites as a part of work of WP7 and in collaboration with Irish Rail. The repository will be relevant for selection, comparison, interpretation, adaptation and assessment of various monitoring aspects around built infrastructure and has a focus on railways, in relation to natural and anthropogenic hazards.

Table of Contents

1. Introduction and Context

With the introduction of a wide range of sensors and networks of sensors, there is an unprecedented opportunity for built infrastructure systems to be monitored and railways are no exception. However, the rate at which such measurements are to be carried out, the locations of measurements, specifications of sensors and the features of interest that are to be detected and estimated pose several challenges, many of which are specific to the structure. Such monitoring can lead to better decision making with lower impact on resources and even safety of workers (many locations can be difficult to access or dangerous). While the demand around many of the decisions taken are not required in real time, monitoring features of interest in real-time can provide a much better control and decision making options. There is a paucity in literature in developing real-time to near real-time monitoring strategies and developing ways to compare them numerically and experimentally, thus creating a repository.

Irrespective of whether monitoring is real-time or not, there are many markers of features of interest. They can be linked to the fundamental physics of the system or just to the data, or both. The markers can be based on time, frequency, or other statistical measures - and can also be a combination of several markers and measures. On the other hand, the features of interests are also required to be chosen carefully. Often, existing literature emphasises on developing a new way of monitoring where the proposed method is shown to be better than other existing methods. This is often unreasonable since this improved performance can often be less effective in another situation or type of dataset. Consequently, it is more important to obtain and compare the performance of relevant features of interest, rather than a single method, marker and feature. This report considers this paradigm shift where the stability, robustness, explainability and adaptability of features and their calibrated performances are more important than a small edge in performance for a narrow zone of data. Thus, this report changes the focus from obtaining the 'best' features to a 'set of acceptable' features whose performance will provide a robust estimate and a clear explanation, and any of the features (or a set) may prevail over the other given a certain dataset, but overall their performance will be comparable.

Finally, there is a clear need to implement monitoring features and their performances for real sites and implementation of them. This implementation is considered with Irish Rail and application in their sites and data, along with some other bridges. The numerical and experimental implementations ensure that the applications are demonstratively carried out and the continuity and connection from and with WP5 and WP7 are carried out . The work also established the developed repository beyond small numerical exercises or controlled laboratory conditions and leads to a translation to practice.

2. Numerical Repository

2.1 Real-Time Detection

In SIRMA, real to near-real time detection is achieved by developing a first order or higher order eigenperturbative approach, subsequently handled with appropriate statistical and related markers.

The schematic of single and multi-channel first order perturbation techniques are presented in Figure 1 using Hankel and data covariance matrices and subsequently computing first order perturbations of the eigenspace using recursive methods (e.g. singular spectrum analysiS (RSSA)s, recursive principal component analysis (RPCA) and damage sensitive features (DSF) linked to them recursively via markers of interest (typically carried out via recursive residual errors). For details, see Bhowmik et al., 2019.

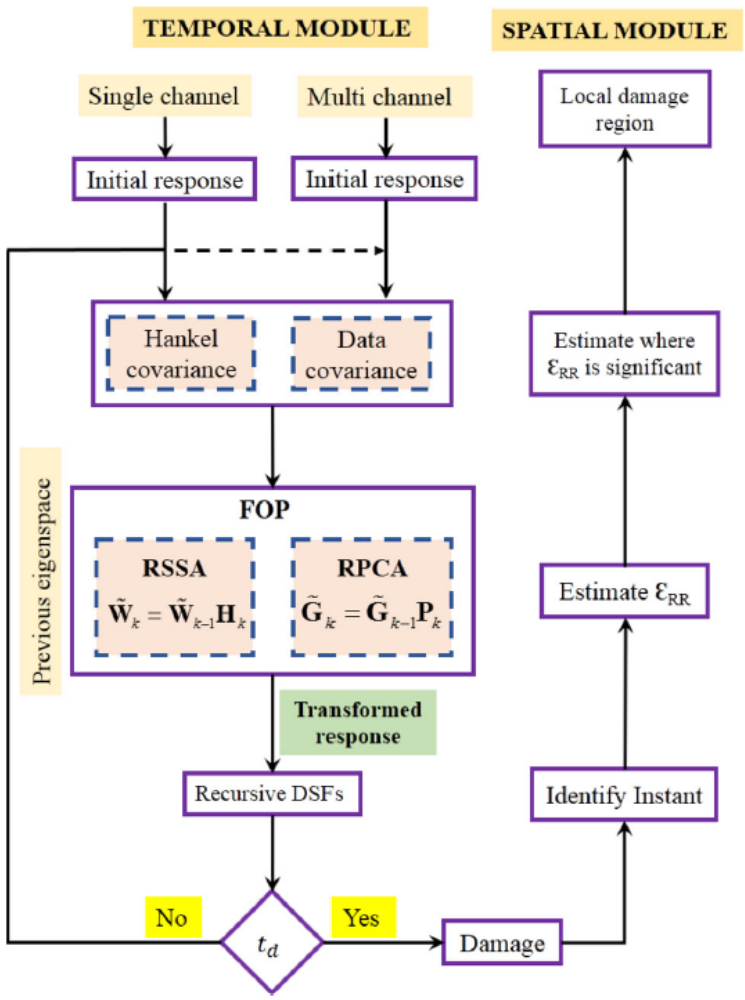


Figure 1: A real-time eigenperturbative approach for detecting features of interest obtained from monitoring

Figure 2 presents damage detection for a 2 story nonlinear Duffing oscillator, for example, with 15% stiffness loss and autocorrelations (AR) as damage indicators in the y axis, along with estimates around recursive residual (RR) errors. This demonstrates the ability of the method of handling nonlinearities.

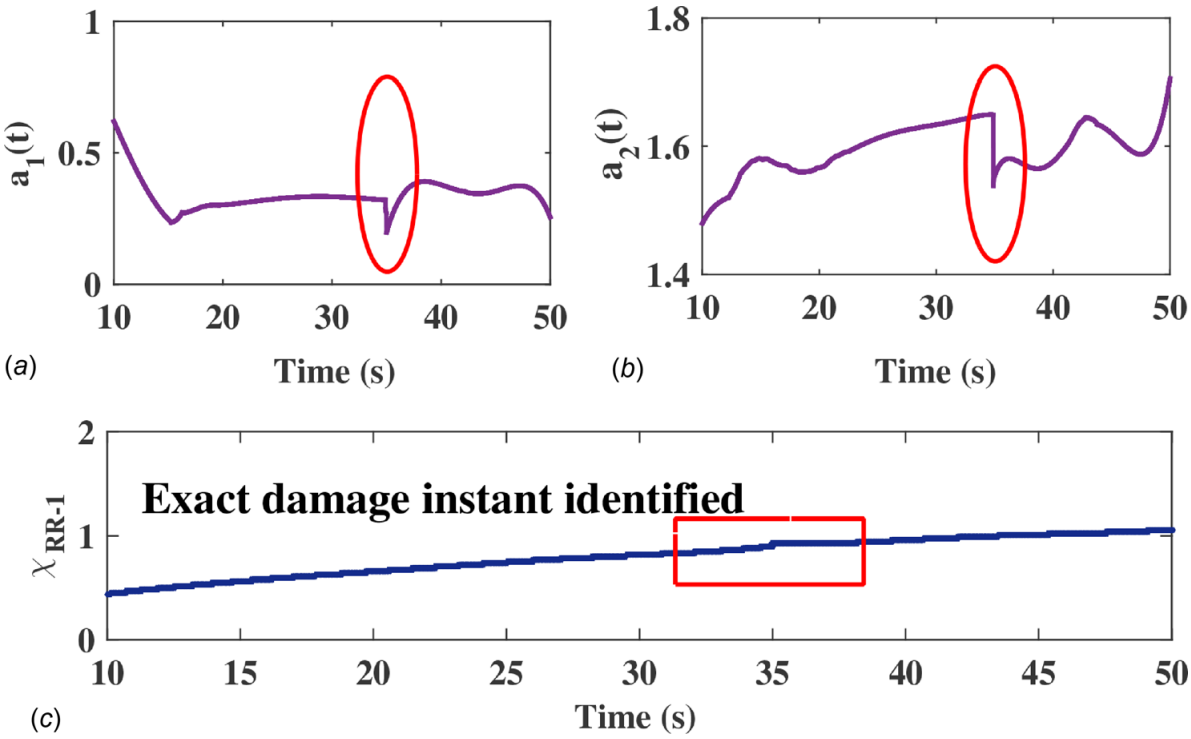


Figure 2. Real-time detection of sudden stiffness change in nonlinear systems

A number of historical laboratory datasets were subsequently tested to link numerics with experiments. An example is provided in Figure 3.

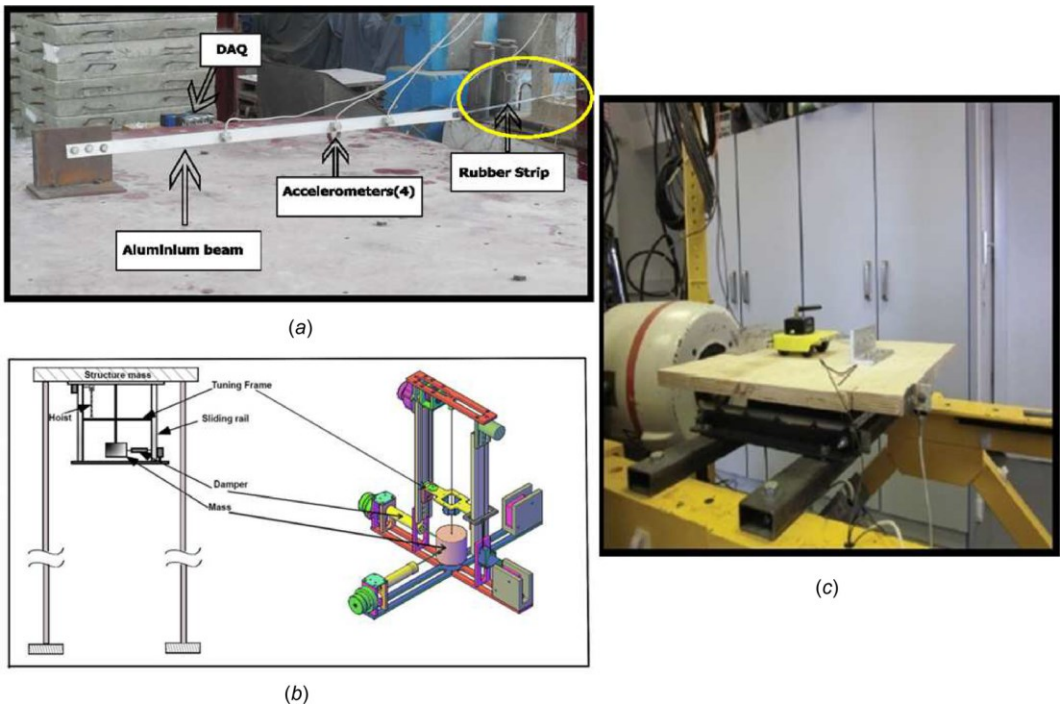


Figure 3. Historical datasets for sudden damage changes in a a) cantilever beam with nonlinear boundary conditions from a rubber strip, b) a tuned mass damper experimental setup representing passive conrol system and c) a Single Degree of Freedom toy cart with sudden changes in stiffness

Figure 4 presents detection of sudden stiffness change in cantilever beam, Figure 5 presents the detection of detuning of tuned mass damper, while Figure 6 presents the detection of sudden stiffness changes in the toy cart experimental example.

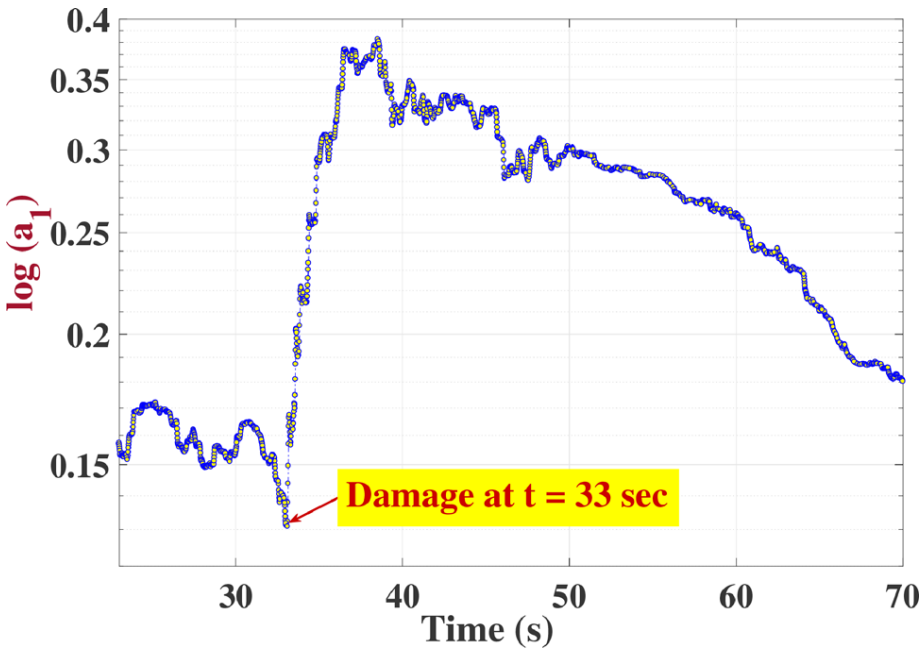


Figure 4. Detection of sudden stiffness change in aluminium beam example

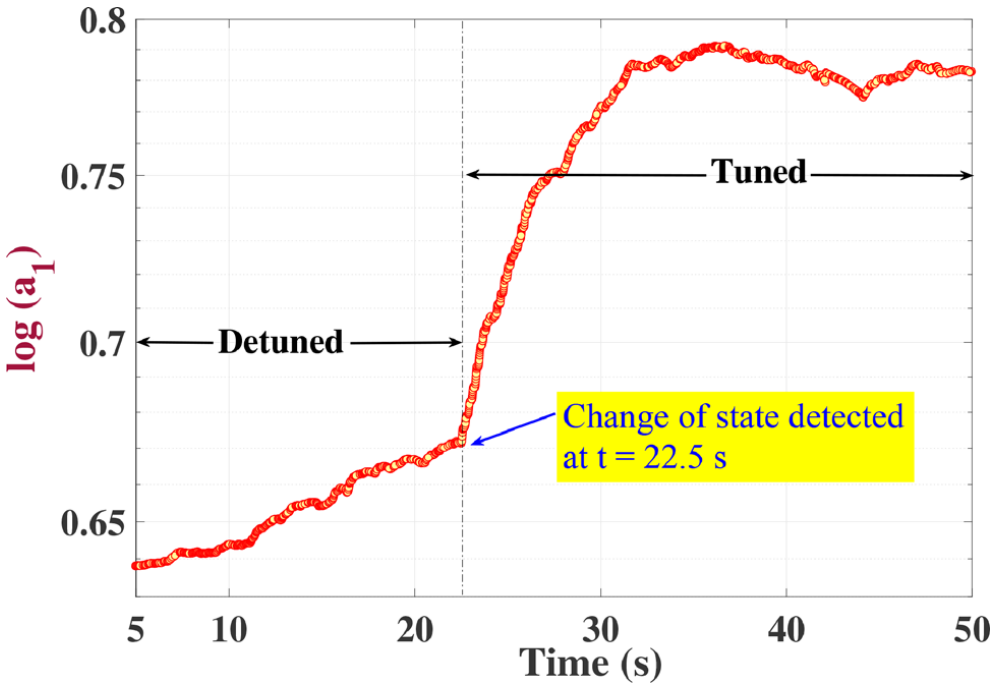


Figure 5. Detection of detuning of tuned mass dampers

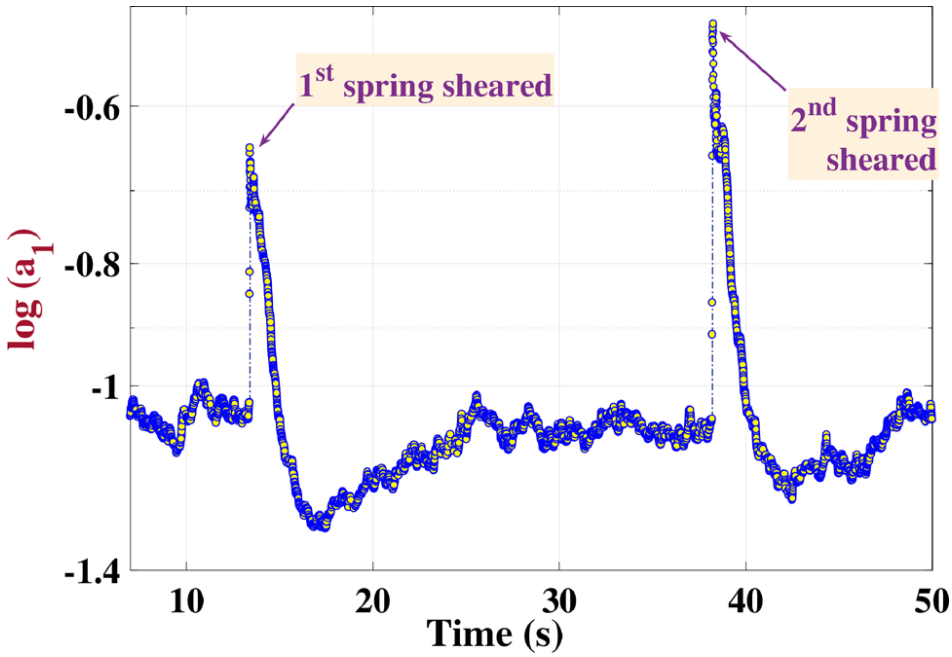


Figure 6. Detection of multiple sudden damages in mass toy cart

Second order methods improving these methods were developed in Mucchielli et al., 2020.

For details, check:

Bhowmik, B., Tripura, T., Hazra, B. and Pakrashi, V., 2020. Real time structural modal identification using recursive canonical correlation analysis and application towards online structural damage detection. Journal of Sound and Vibration, 468, p.115101.

Bhowmik B, Tripura T, Hazra B and Pakrashi V. (2020). Robust linear and nonlinear structural damage detection using recursive canonical correlation analysis. Mechanical Systems and Signal Processing, 136,106499.

Bhowmik, B., Panda, S., Hazra, B. and Pakrashi, V., 2021. Feedback-driven error-corrected single-sensor analytics for real-time condition monitoring. International Journal of Mechanical Sciences, p.106898.

Mucchielli, P., Bhowmik, B., Hazra, B. and Pakrashi, V., 2020. Higher-order stabilized perturbation for recursive eigen-decomposition estimation. Journal of Vibration and Acoustics, 142(6).

Bhowmik, Basuraj, Budhaditya Hazra, and Vikram Pakrashi. Real-Time Structural Health Monitoring of Vibrating Systems. CRC Press, 2022.

Bhowmik, B., Tripura, T., Hazra, B., & Pakrashi, V. (2019). First-order eigen-perturbation techniques for real-time damage detection of vibrating systems: Theory and applications. Applied Mechanics Reviews, 71(6).

2.2 Time Series Approaches for Data Imputation

Several data is often missing at random or more frequently, in chunks, from long term monitoring of data. To address analysis of such data with missing zones, a data imputation approach is considered.

Several methods are considered in this regard using time series methods with a range of complexity and detail including Series Average, Persistence, Moving Average, Interpolation, ARIMA, Local Linear Trend, Dynamic Time Warping and Dynamic Linear Model (DLM) and

Figure7 shows the performance of DLM for missing data in a continuously monitored bridge impacted by a low loader and the subsequently repaired.

More detail on the bridge is presented in section 3, but this sub-section focuses on the numerical approach towards missing data imputation, using examples that are from real ocurreneces.

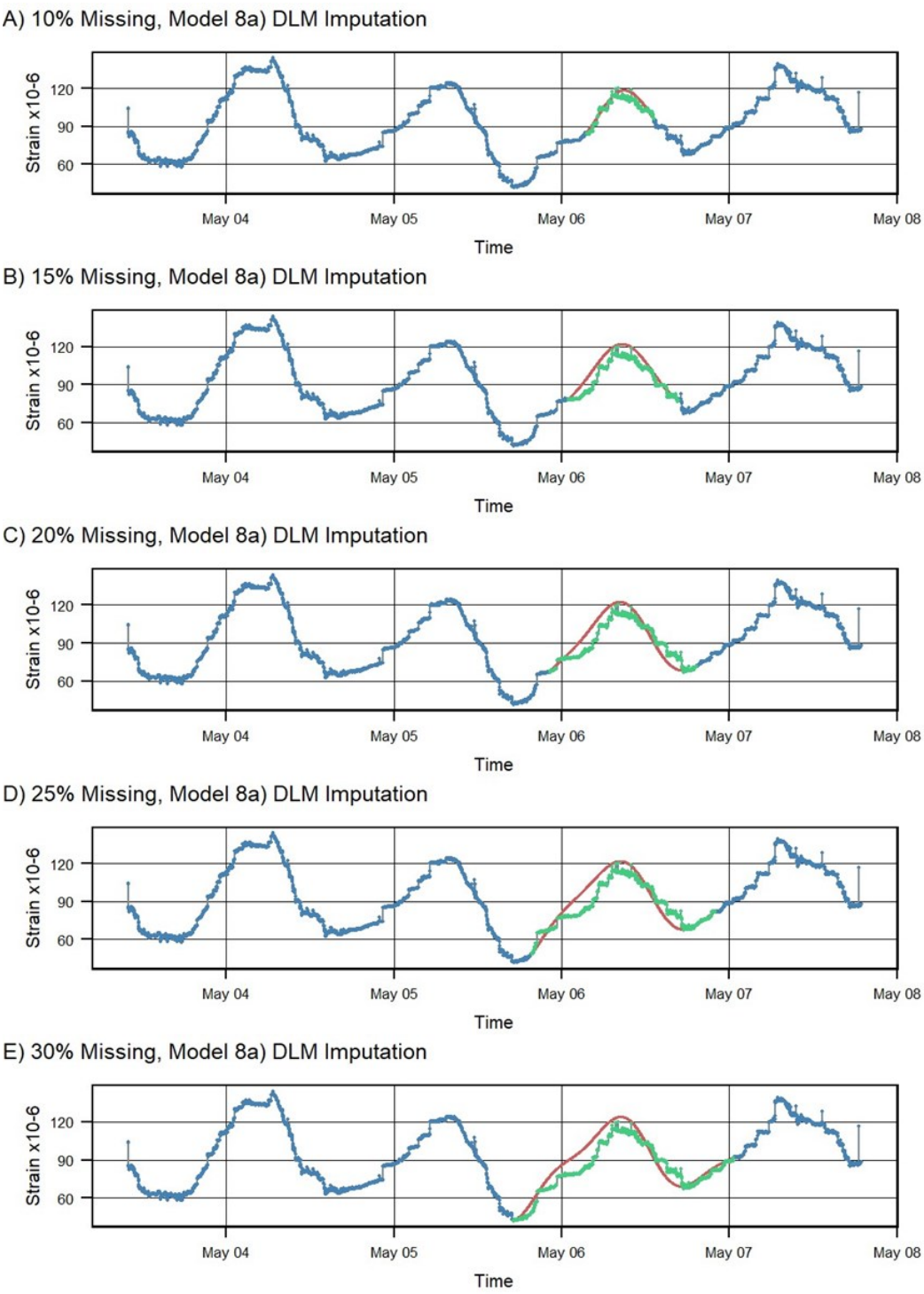


Figure 7. Data imputation using Dynamic Linear Modeling

For data missing at random, similar results are obtained for DLM and presented in Figure 8.

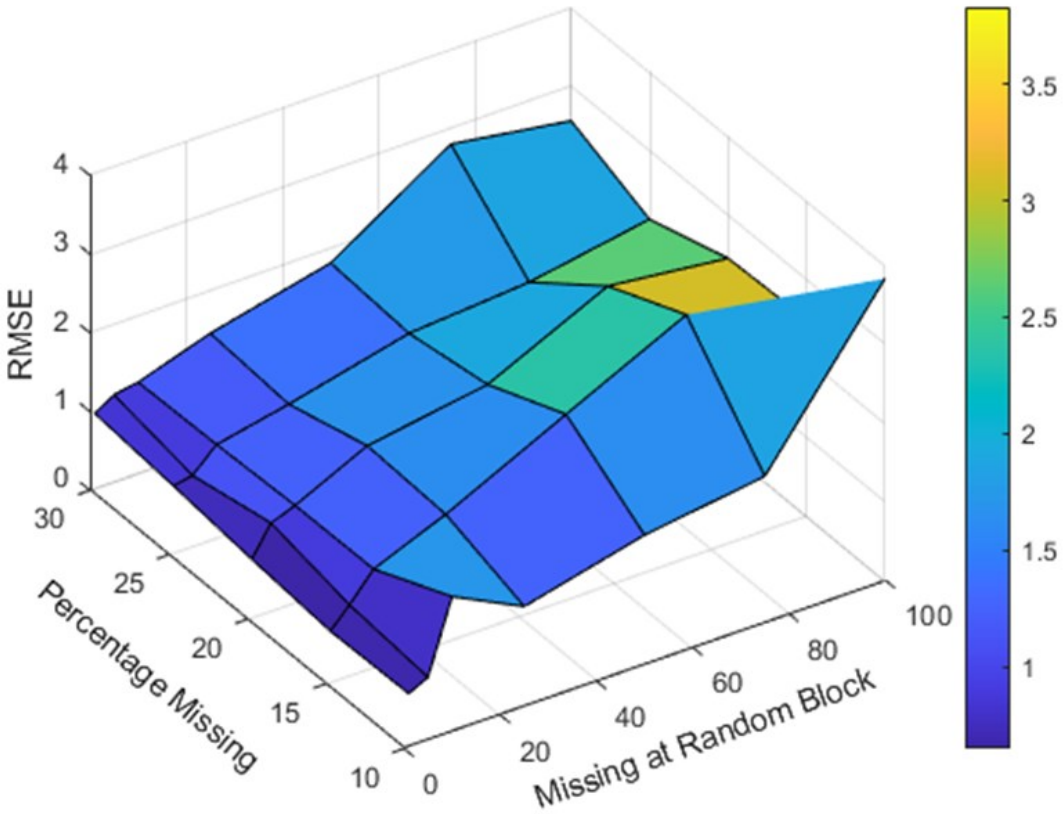


Figure 8. Data imputation using Dynamic Linear Modeling

2.3 Machine Learning, Artificial Intelligence and Features of Interest

Machine Learining and Artificial Intelligence have expanded themselves to all sectors and railway infrastructure is no alien to these ideas. However, for realistic datasets, their performance, interpretation and repeatability suffer and consequently their testing is carried out in conjunction with experimental and implementation studies, linking WP5 asn WP7 clearly.

Under such circumstances, on the numerical side, it is the choice of analysis and features of interest that are more relevant. Section 3 is thus recommended for further details on the topic and the methods that were compared.

Here, several features were investigated and a representative sample list is presented in Figure 9 to demonstrate how numerical analyses informed and developed the core aspect of experimental evidence base and the full scale implementations.

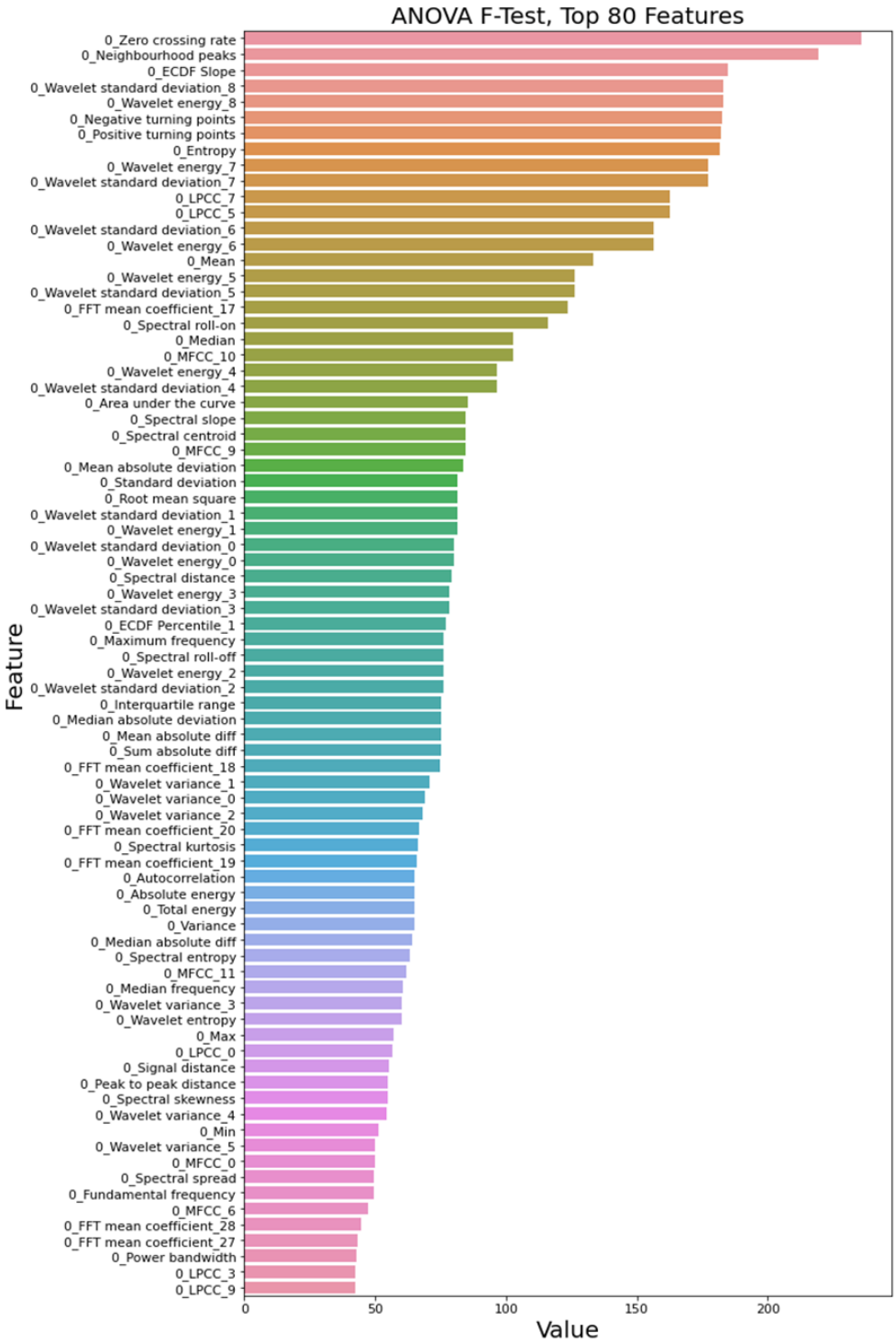


Figure 9. ANOVA ranking of top 80 features of various sources

3. Experimental Repository

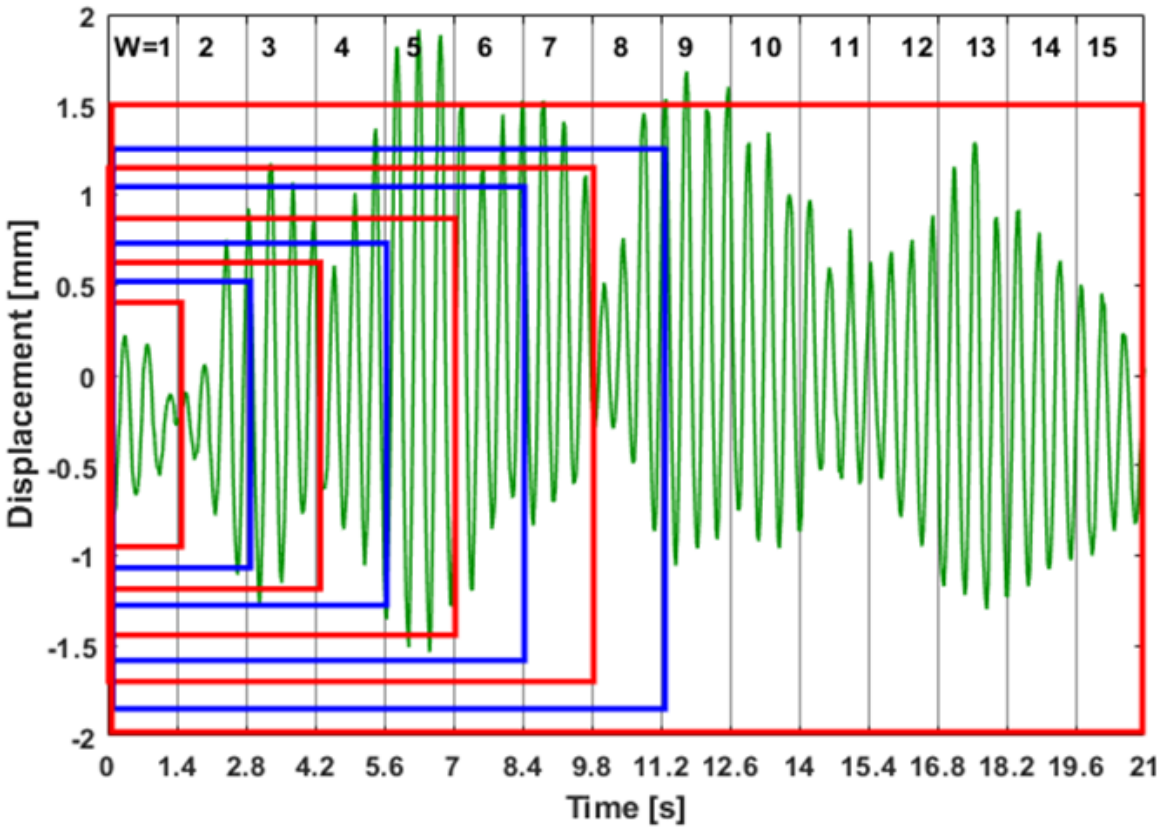
3.1 Real-Time Detection

Real-time detection needs were addressed through eigenperturbation techniques in theory and experiments were carried out. Here, in full-scale examples, the Daly's bridge in Ireland (O'Donnell et al., 2017) and its tests were used.

The Daly's bridge is an iconic steel suspension footbridge in Cork, Ireland, popularly known as the 'Shakey' bridge, for its discernible movement under pedestrian loading. The structural parameters of this transport system are identified using the video analysis of the dynamic deflection under excitation from traversing pedestrians. A wireless sensor network was installed throughout the structure to record the vibration data sampled at 50 Hz, with a range of ±2g. The video camera positioned at the riverbank aided in visually tracking the video analysis at certain pre-selected nodes, which is shown in Figure 10.

Figure 10. Non-Contact measurements on Daly's Bridge, Ireland

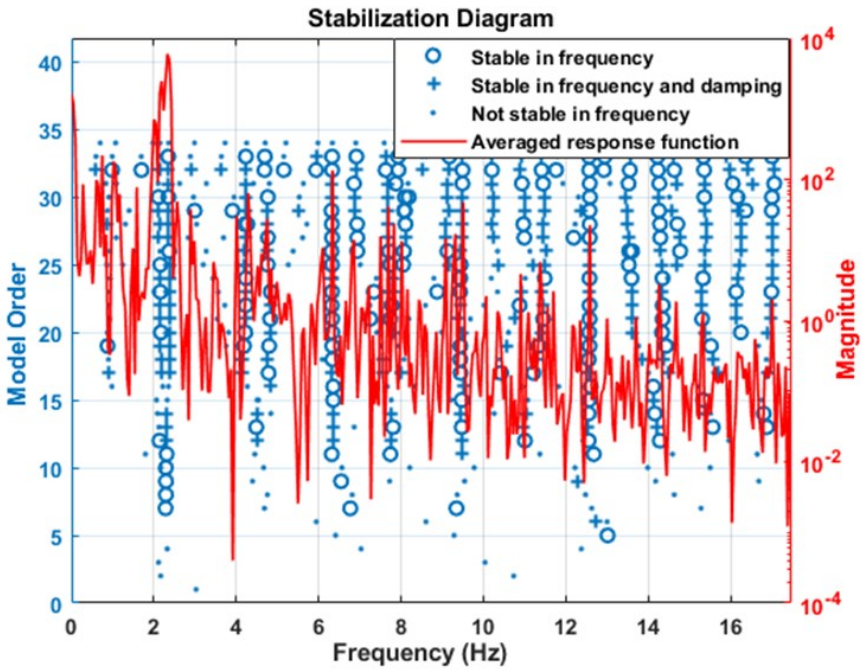
For the present study, the vibration responses gathered for the monitored period of approximately was considered for analysis. The structural responses to a pedestrian walking over the bridge is analysed in pre-selected window length for estimating the modal parameters. Automated windows (W) of 50 samples stretched over the entire output response is illustrated in Figure 11.



. **Figure 11.** Vibration response of Daly's bridge in multiple windows

The spectral estimate for the complete set of responses obtained from bridge dynamics is shown in Figure 12. While the presence of closely spaced modes is evident from the figure, the implementation of an automated approach enables the estimation to be implemented without any discrepancies. In order to avoid overestimation of the damping ratio, the windows are automated to have the same number of samples throughout, which counters the assumed periodicity of spectral estimates within a finite measurement time.

Spurious frequencies arising due to closely spaced modes impair the estimation ability of the proposed ET-FDD method, leading to over estimation of damping ratios. Cases where the first singular value and neighbouring values indicate a peak corresponding to a certain frequency manifests the occurrence of a harmonic instead of an actual structural response. In order to avoid this, a stabilization diagram shown in Figure 13 indicates the chosen range where the estimate is stable in both frequency and damping. From the figure, frequencies of 1.9 Hz, 2.19 Hz and 2.32 Hz are found to be stable and therefore, designated as modes of significance.



. **Figure 12.** Spectral Estimate outputs from Daly's Bridge

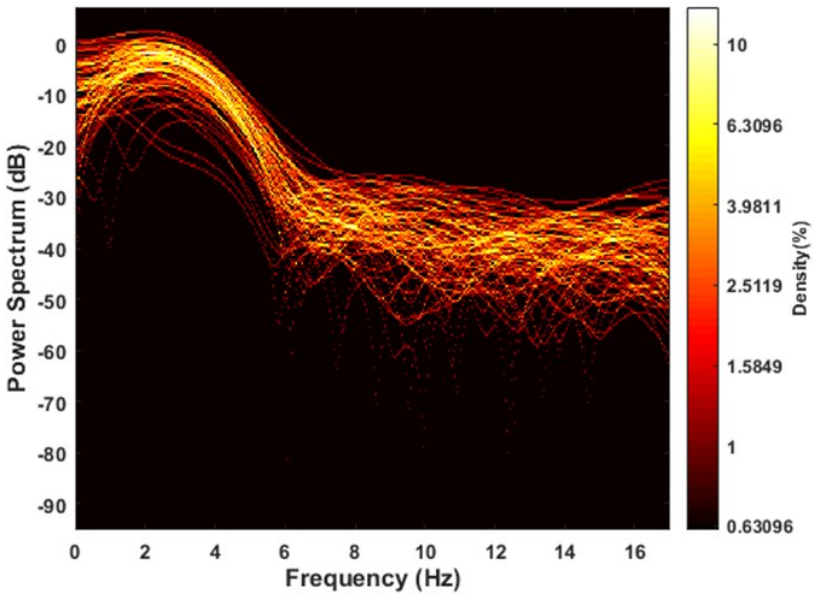


Figure 13. Vibration response of Daly's bridge in multiple windows

The windowed response obtained from the automated system is used to estimate the damping ratios using the basic TDD approach. Windowed data of 50 samples each are analysed in a real time framework to provide estimates of damping ratios corresponding to

each mode. Theoretical estimations of modal damping ratios indicate 2%,3% and 2% damping in the first three modes, respectively.

The windowed data is provided as input to the proposed automated real time method. The damping is estimated from the logarithmic envelope of the correlation function for each window. The evolution of the damping estimates for each window is graphically illustrated in Figure 14. However, it should be realized that an improved damping estimate for higher modes requires records of longer duration, where the loading can be in the form of repeated trials of pedestrians walking over the bridge.

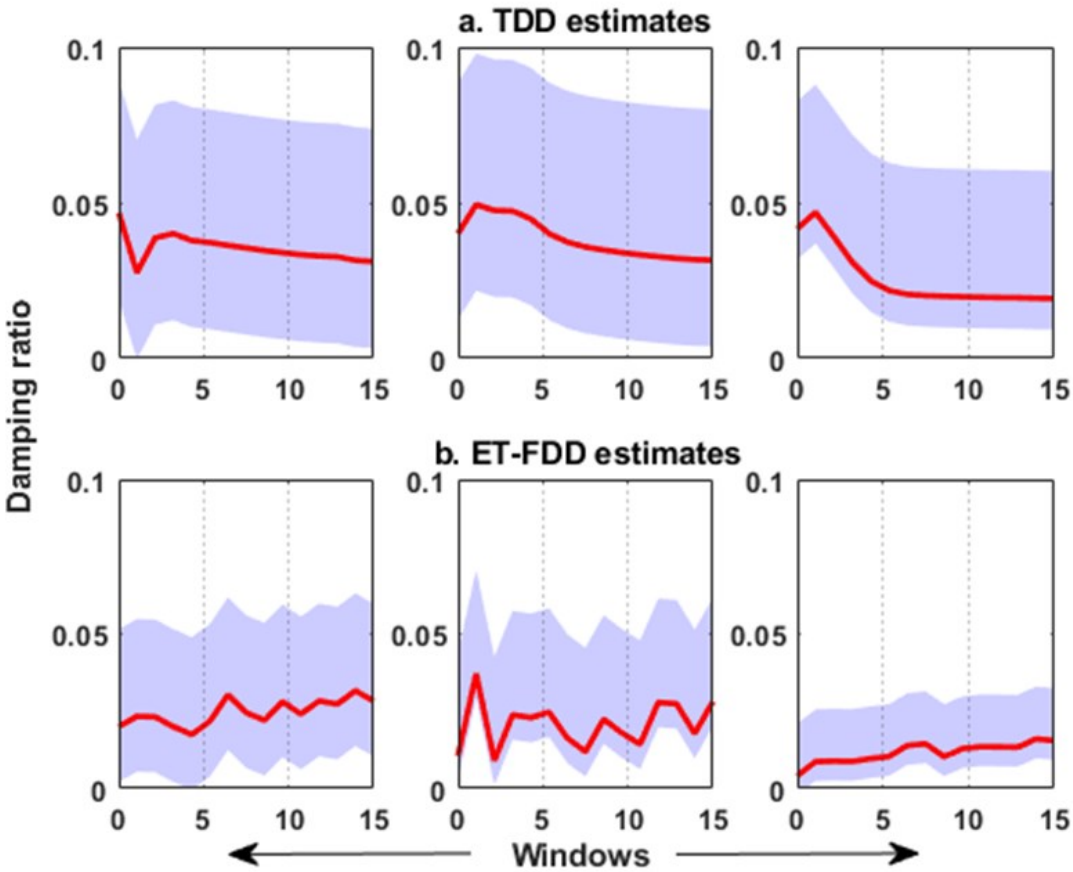


Figure 14. Evolution of damping ratios from obtained results

An important consideration related to the damping ratio estimates lie in the resolution of samples adopted during the PSD matrix evaluation. The PSD matrix, computed at each sampled window length, fulfils all the properties required for correct working of the proposed ET-FDD technique, which include real diagonal terms and complex conjugate off-diagonal entities, thereby leading to a Hermitian matrix. The use of correct sampling resolution in an automated real time framework affects directly the number of spectral bells that are available prior to the projection into the time domain. Especially with short structural recordings the resolution can be enhanced by increasing the number of samples corresponding to each chosen window. For cases where the enhancement of sampling resolution is unattainable, a

zero-excitation time window added at the end (zero-padding) of the recordings can increase the duration of the response.

See also for details: Bhowmik, Basuraj, et al. Damping estimation of a pedestrian footbridge–an enhanced frequency-domain automated approach. Journal of Vibroengineering 23.1 (2021): 14-25.

3.2 Time Series Approaches

A dynamic Harmonic Regression approach was created for monitoring slowly sampled structures, especially in the context of strain measurements. This was applied to the monitoring of an impact damaged bridge and details are available in Buckley et al., 2021. These data often have parts missing and the forecast or backcasting approaches thus require a time series solution. Figure 15 presents the overall way of handling such a situation, The DHR methodology is applied to strain data recorded at minute intervals from an impact damaged prestressed bridge (Pakrashi et al., (2013)) between 08:19hrs on the 28/04/2010 and 18:51hrs on the 7/05/2010, with a total of 12,011 data points of a minute interval.

The Brownsbarn bridge (Figure 16) is a two-span continuous slab-girder bridge consisting of six precast prestressed U8 simply supported concrete beams of 27.35m length and without skew. It is connected by a continuity diaphragm and spans the national road N7 in the Republic of Ireland connecting its two largest cities. The bridge was damaged after being struck by a low-loader carrying an excavator passing underneath the bridge. The reinforced concrete piers are integral to the deck and the ends of the bridge are simply supported. The abutments are made of reinforced concrete. The continuity diaphragm is connected to the U8 beams through steel plates of dimension 300mmx30mmx1700mm.

The monitoring points were chosen so that local strains from both the damaged and undamaged beams can be recorded so that a comparison can be made during the strength gain period post repair and before re-opening of the bridge for normal operations. There are three monitoring points at the centre (MP2, MP4, and MP5) and at the two ends of the damage (MP1 and MP3), at the centre of the two undamaged beams, and the two sides of the damaged beams. An example of strain measurement data is provided in Figure 17. Environmental challenges of such monitoring are reflected in Figure 18 where strain versus temperature data for a healthy period is presented.

Figure 19 presents the application of the dynamic harmonic regression model created while Figure 20 demonstrates through backcasting how such model can be used for anomaly and damage detection.

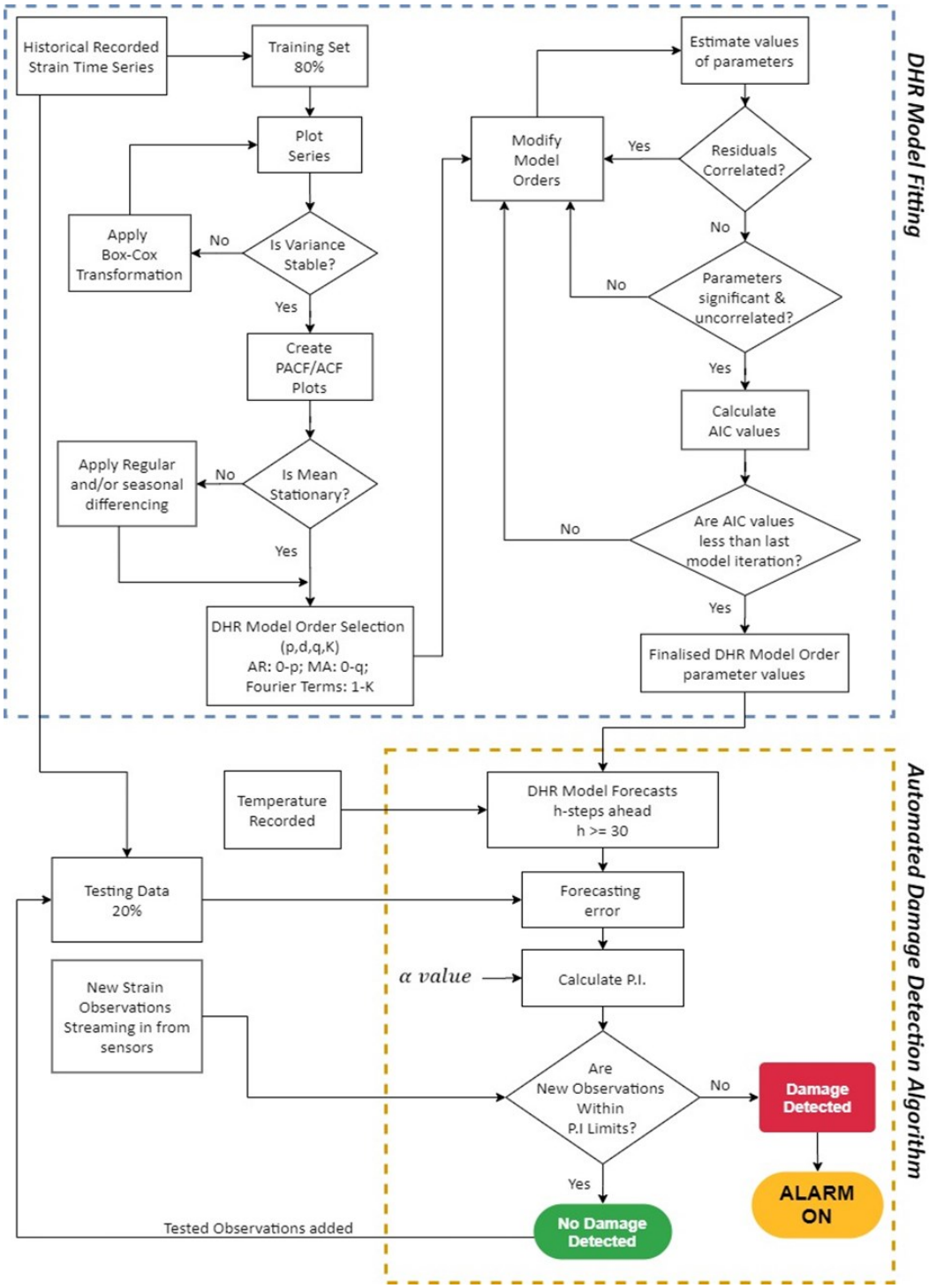


Figure 15. Flow Chart of Dynamic Harmonic Regression Model and Automated Damage Detection Algorithm

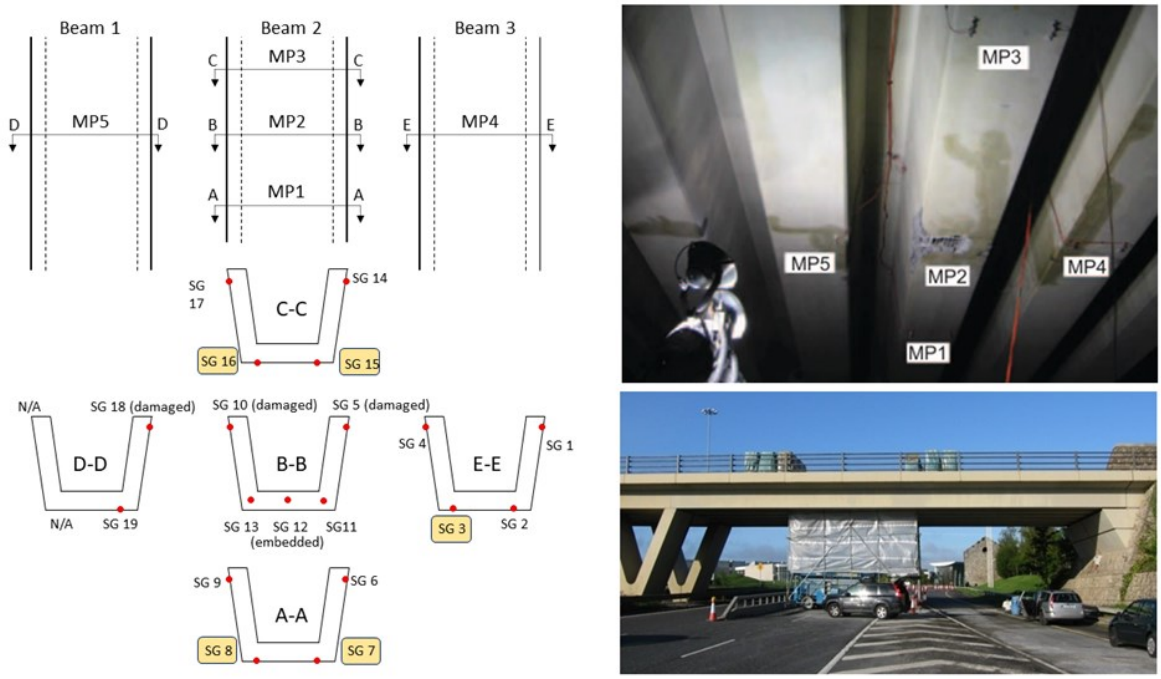


Figure 16. Brownsbarn Bridge Rehabilitation in Ireland and Related Sensor Placement

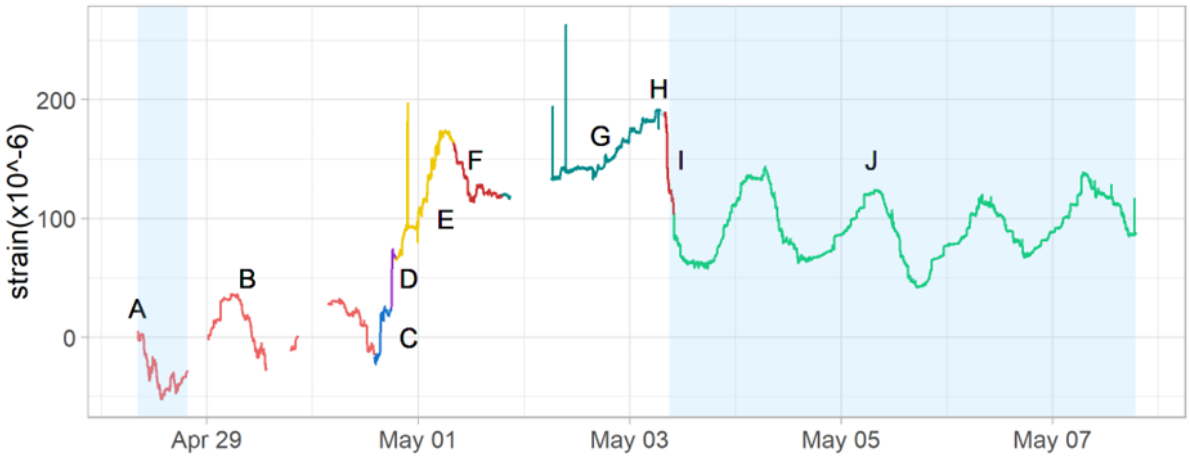


Figure 17. Strain measurement data from a representative gauge

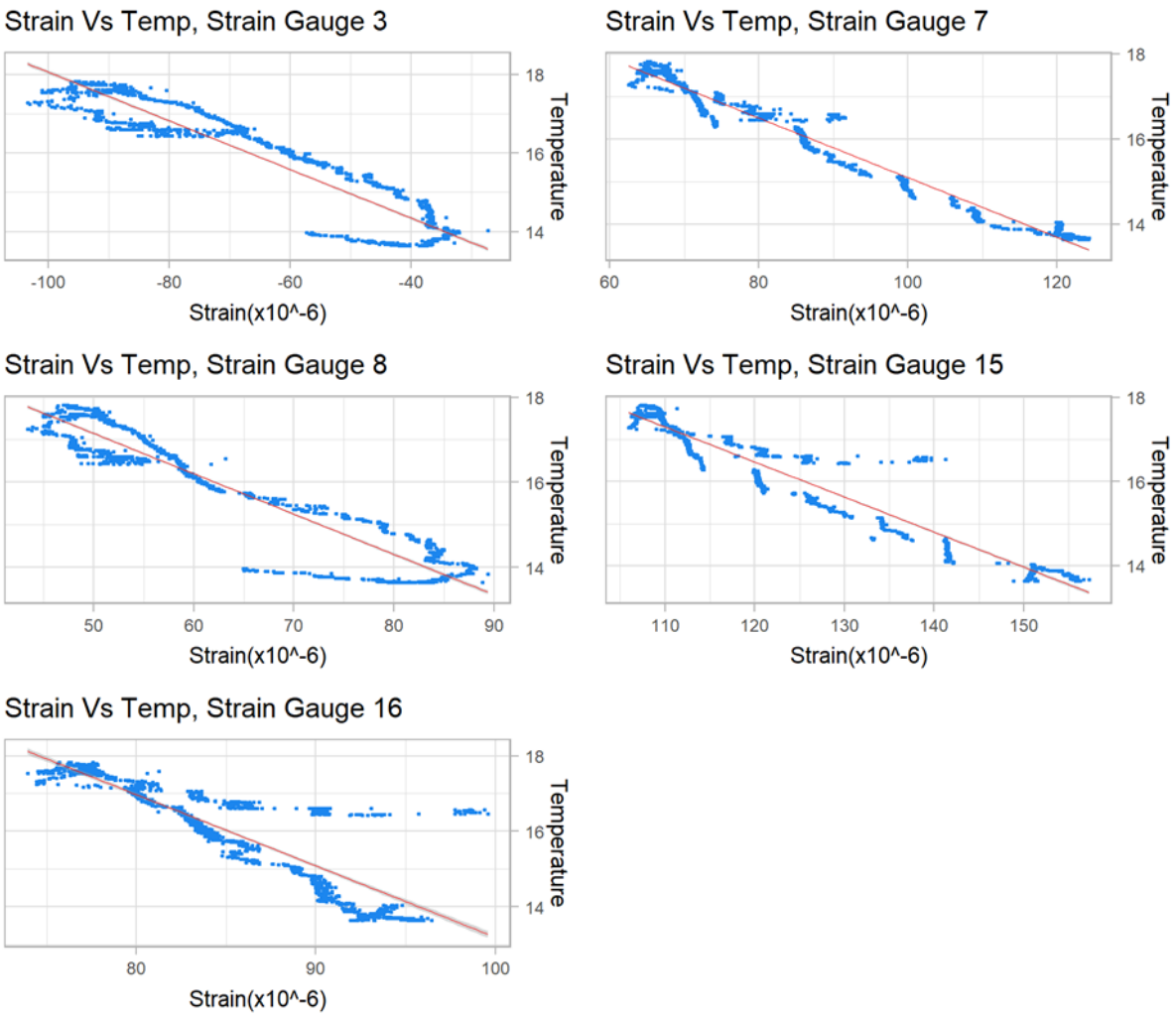


Figure 18. Strain Vs Temperature in Healthy Period

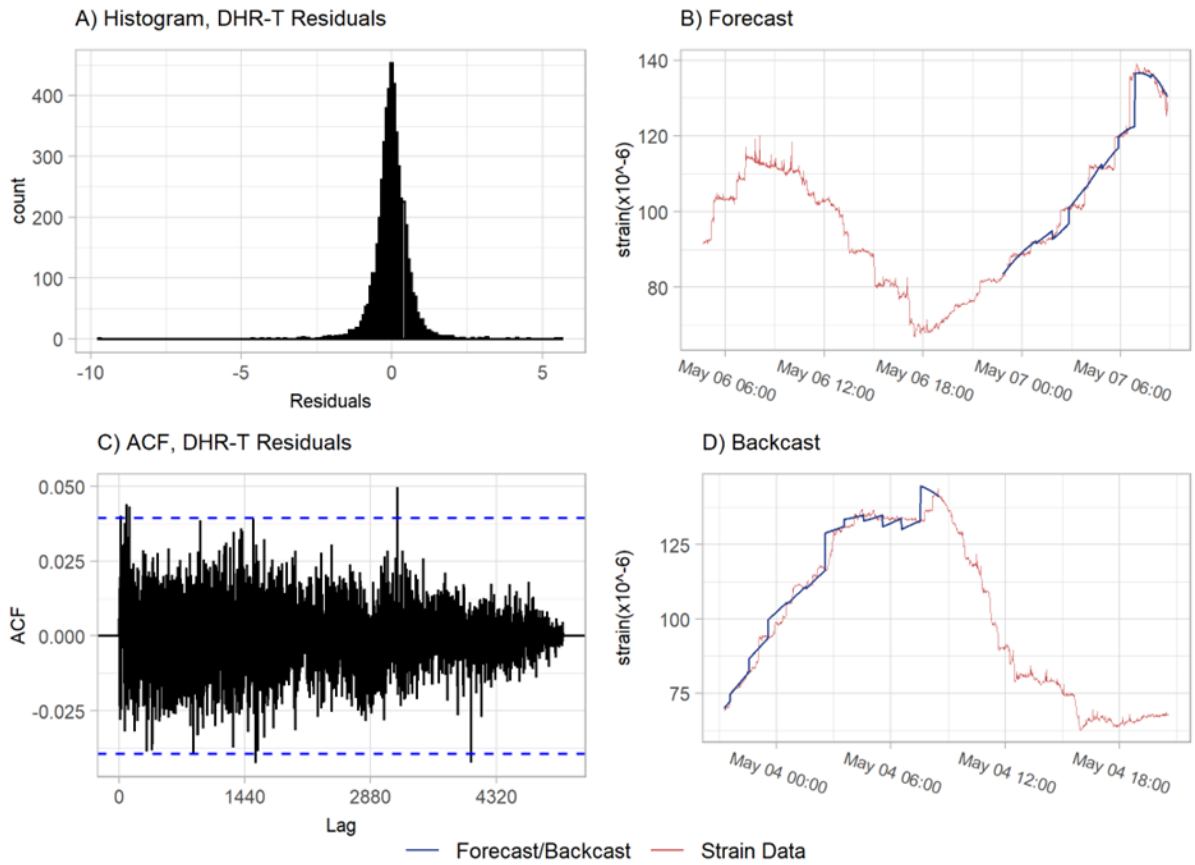


Figure 19.. Analysis of DHR-T model applied to strain gauge 7: (a) histogram of residuals, (b) forecast onto validation data set, (c) residual ACF plot and (d) backcast onto backcast test data set.

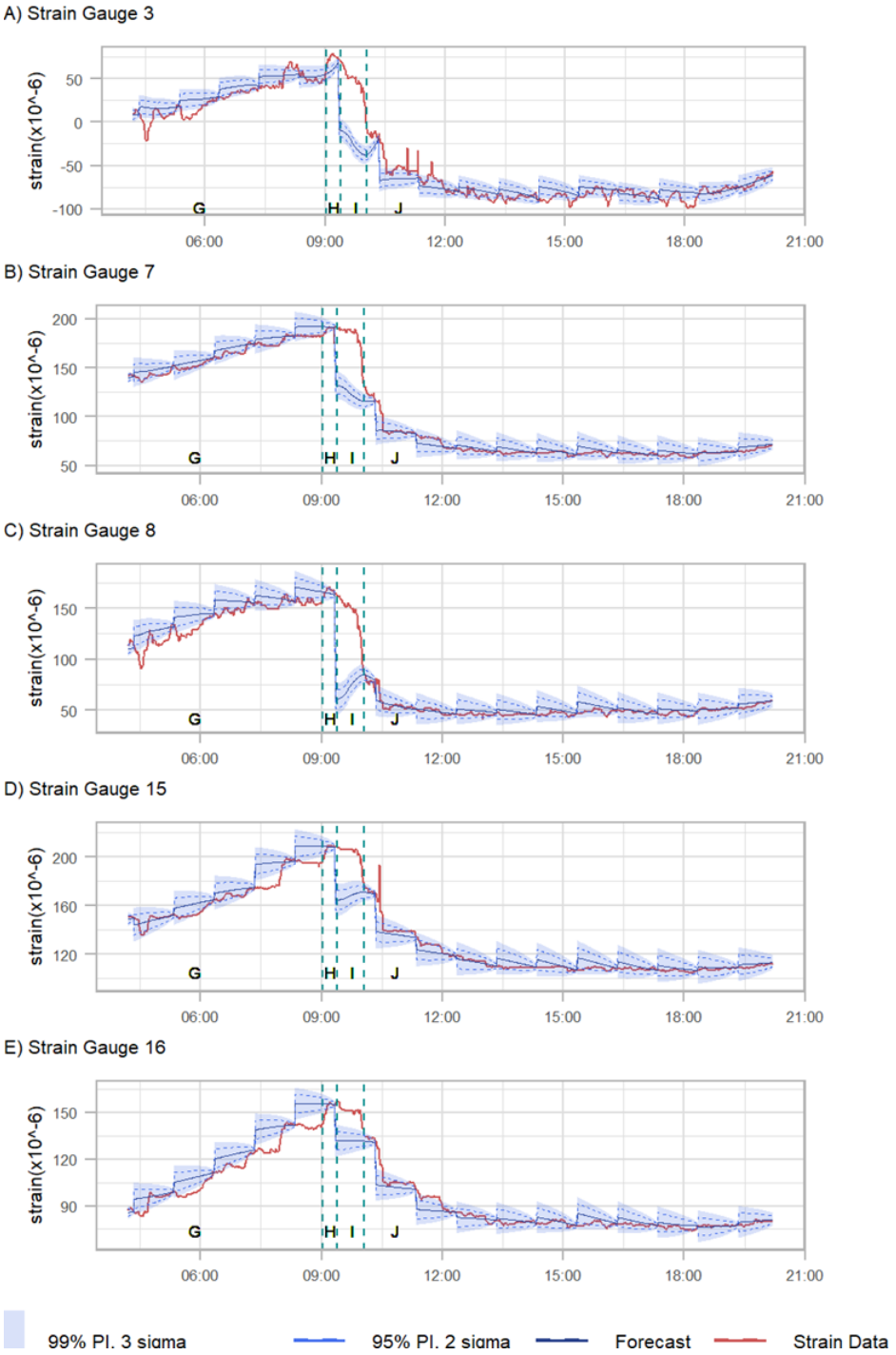


Figure 20. 60-step backcasts from healthy (further strength gain -J) period onto removal of load (I) and periods of concrete hardening (H and G) periods.

See more in:

Pakrashi V, Harkin J, Kelly J, Farrell A, and Nanukuttan S. (2013). Monitoring and Repair of an Impact Damaged Prestressed Concrete Bridge, Proceedings of the Institute of Civil Engineers, Journal of Bridge Engineering, 166(1), 16-29

Buckley B, Ghosh B and Pakrashi V. (2021). A Dynamic Harmonic Regression Approach for Structural Health Monitoring. Structural Health Monitoring, https://doi.org/10.1177/1475921720981735

3.3 Feature Selection

What feature to choose and how to address their performance has always been an important question in structural health monitoring. In this regard, a comprehensive analysis was carried out on full scale tests on the well known Z24 and S101 data. The S101 Bridge (Figure 21) was pre-stressed 3-span flyover near Vienna in Austria that had a main span of 32m and two 12m side spans. In 2008, the S101 Bridge was to be replaced due to insufficient carrying capacity and deteriorating structural condition, identified from visual inspection.

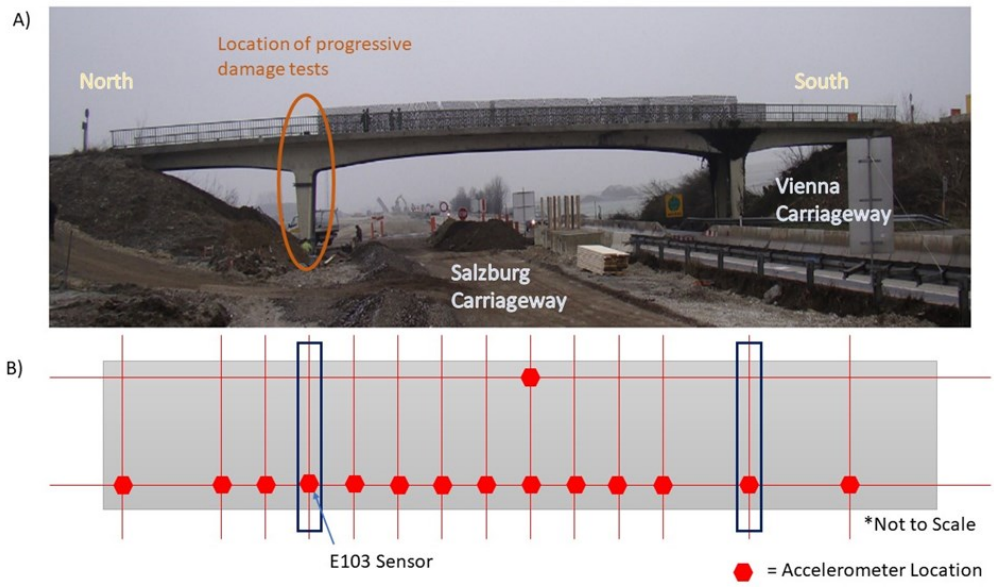


Figure 21. a) S101 Bridge b) sensor location grid, adapted from (VCE. Progressive Damage Test S101 Flyover Reibersdorf (draft), Tech. Report 08/2308, (2009))

Progressive damage was conducted on the S101 Bridge across 3 days from 17:16 on the 10/12/2008 to 11:04:00 on the 13/12/2008. During this period, the bridge was closed to traffic. Therefore, asides from induced damage events, bridge excitations were mainly ambient. One traffic lane beneath the bridge was kept in use. There are 14 sensors located on the east side and one reference sensor on the west side of the bridge with data recorded at a sampling rate of 500Hz. Minimal temperature variation was observed throughout the test

duration as sub-zero temperatures were kept within a 3 to 4 degree range, day and night, due to persistent heavy cloud cover.

This event timeline (Buckley et al., 2022) is organised into 12 separate sequences and analysed as separate damage classifications. Each sequence corresponds to a damage state caused by an action on the bridge and any subsequent monitoring before the next action.

The well known Z24 dataset was recorded from a pre-stressed concrete, 14-30-14m span, highway bridge in Switzerland, (Figure 22). Two rows of three pinned concrete columns are supporting the bridge at the endpoints and two concrete piers clamped into the girders are situated at the end points of the main span. Although there were no known structural problems with the bridge, it had to be demolished because a new railway next to the highway required a bridge with a larger side span. A detailed description of the monitoring can be found in (Peeters and De Roeck, (2001)).

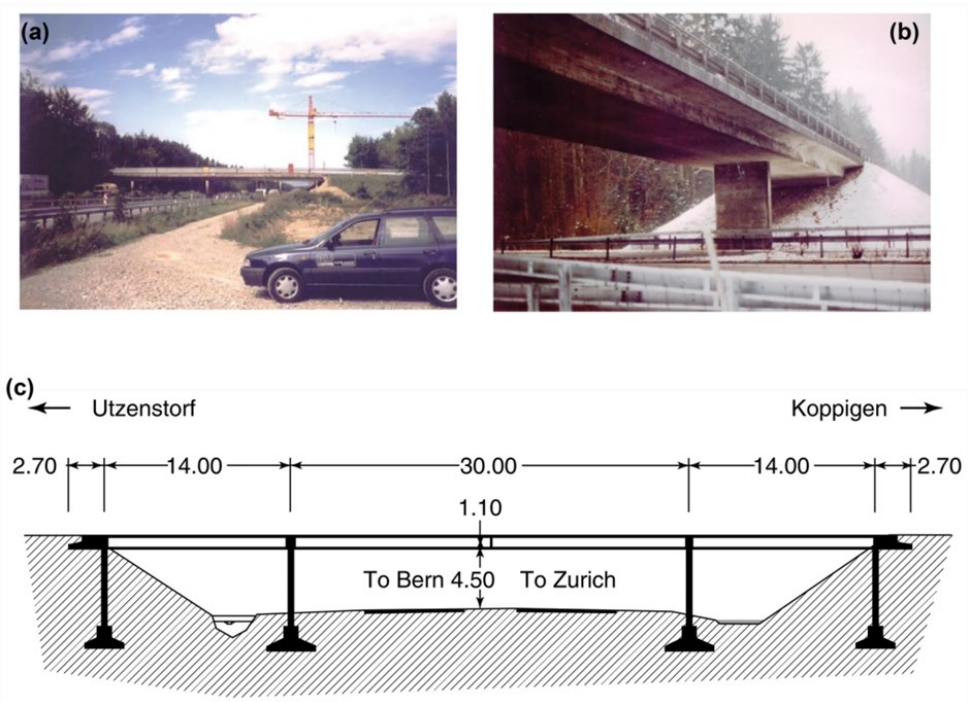


Figure 22. (a) Z24 bridge (b) close up view of bridge (c) longitudinal section and plan view of Z24 bridge (Maeck and De Roeck, (2003))

Prior to its demolition, it was monitored for almost an entire year, from 10th November 1997 to the 10th September 1998, using a network of accelerometers and environmental sensors measuring air temperature, soil temperature, humidity etc.

The almost year long period of passive monitoring is described as the Environmental Monitoring System (EMS). At the end of the monitoring campaign, an extensive network of accelerometers were placed across the bridge and the bridge was subjected to 16 Progressive Damage Tests (PDTs). Due to the lack of long term monitoring data where a healthy structure experiences damage, the Z24 dataset has become the benchmark dataset in the field of SHM over the last 20 years.

A comprehensive spearman correlation plot for features of S101 data is presented in Figure 23 while that for Z24 is in Figure 24. The outcomes demonstrate how, rather than trying to find the best performance, it is appropriate and even more consistent to look for a set of features that perform reasonably well and then the outcomes of assessment are robust. Within a range of datasets, the choice of a set of individual features will lead to results that might prevail over others slightly, but the features to avoid are well established. This leads to a more stable and explainable way of assessing the features and the monitoring aspects they link to.

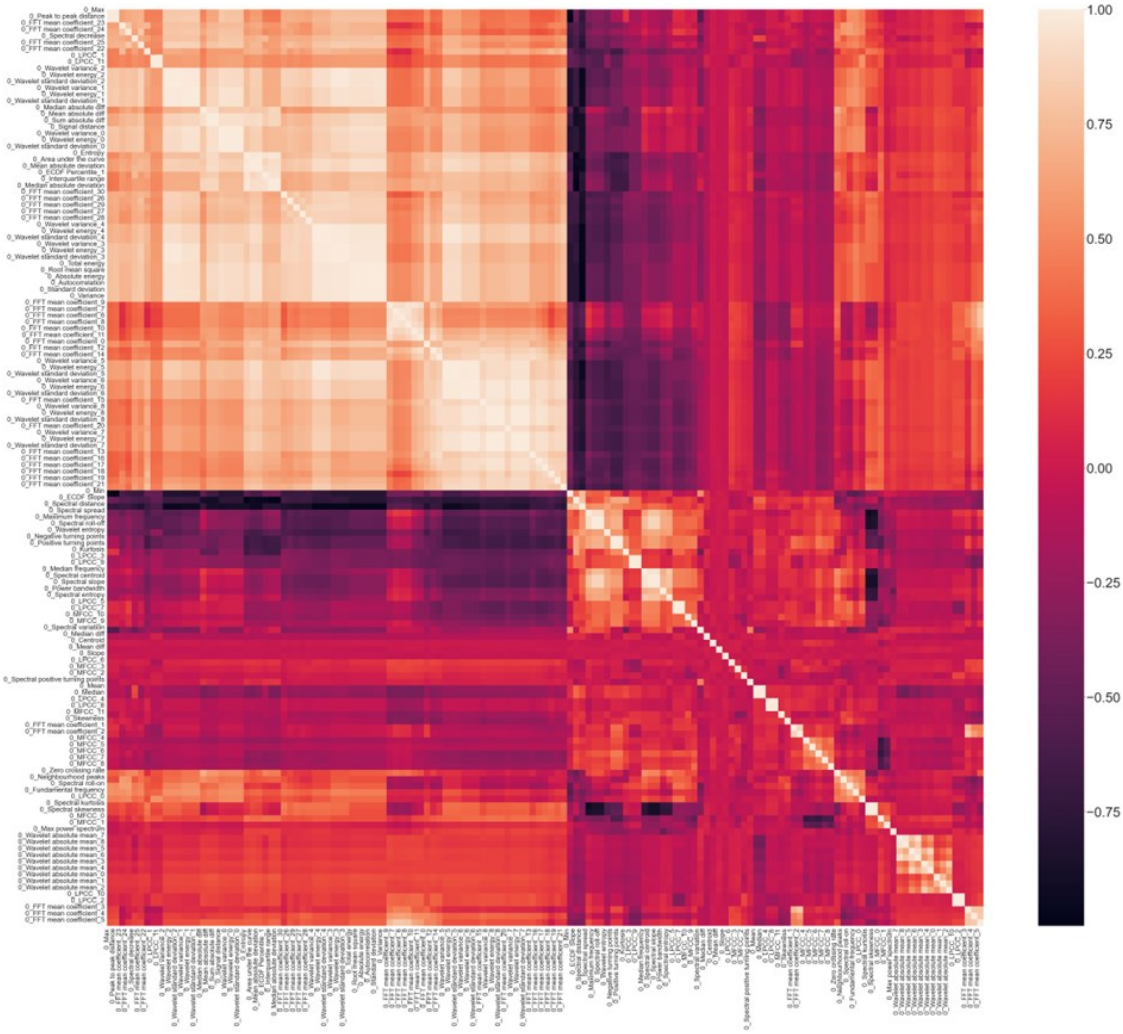


Figure 23. Spearman rank correlation for features related to S101 bridge monitoring

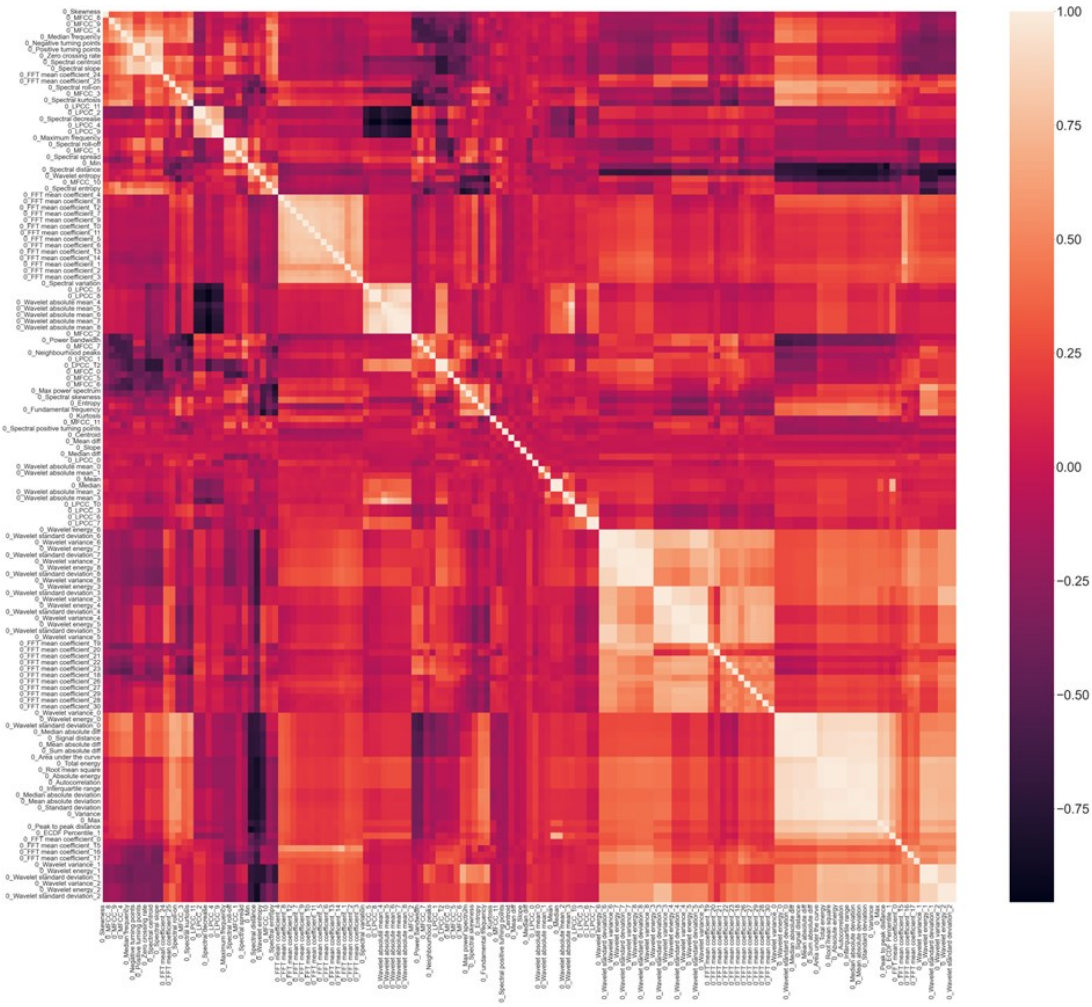


Figure 24. Spearman rank correlation for features related to Z24 bridge monitoring

3.4 Machine Learning and Artificial Intelligence

S101 has significantly imbalanced data as compared to Z24 and so this gives an opportunity to compare Machine Learning and Artificial Intelligence approaches, their comparisons and limitations.

A stratified cross validation procedure is implemented for this purpose and a standard 5-fold stratified cross validation is chosen which results in an 80-20 train-test split across each fold and each damage state. The data is not shuffled so that the time sequence within each class is maintained.Support Vector Machine (SVM), Bagged Tree, Random Forest, K neighbours, and Naïve Bayes were used and optimal hyperpaprameters were chosen from the data. Rather than using a nested gridsearch within each cross-validation fold when modelling the data, the parameters that maximise the classification prediction performance are chosen in advance from the entire dataset to ensure comparability of models across different cross validation folds for each feature selection method. To create a baseline against which the reduced feature sets can be compared, the classification methods presented in the methodology are first applied to the entire feature set. Figure 25 shows the results of various approaches for S101 bridge while Figure 26 shows the same for Z24.

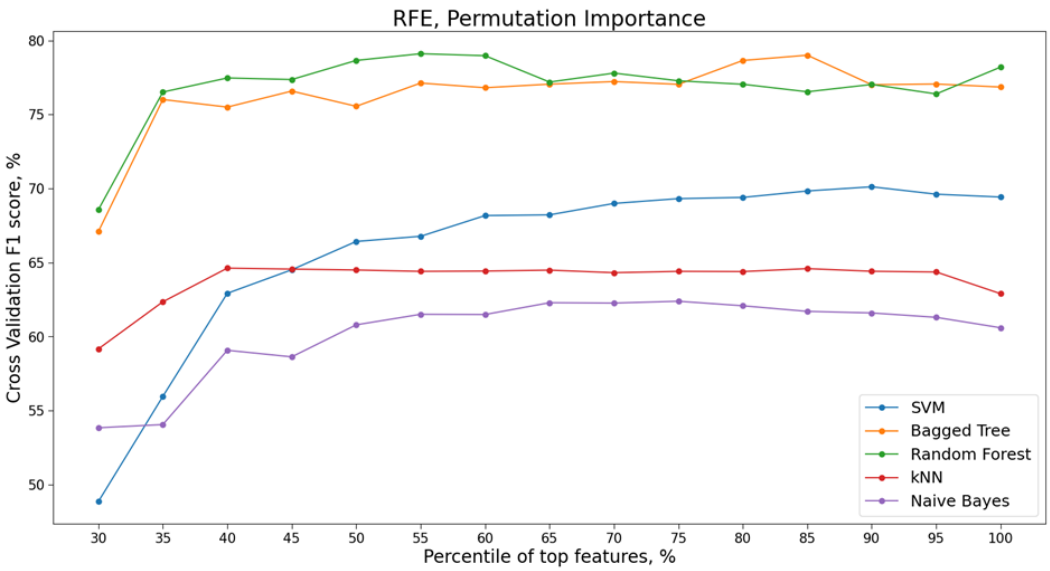


Figure 25. Recursive Feature Elimination (RFE) for varying percentiles of decorrelated feature set, ranked by permutation importance, S101 dataset

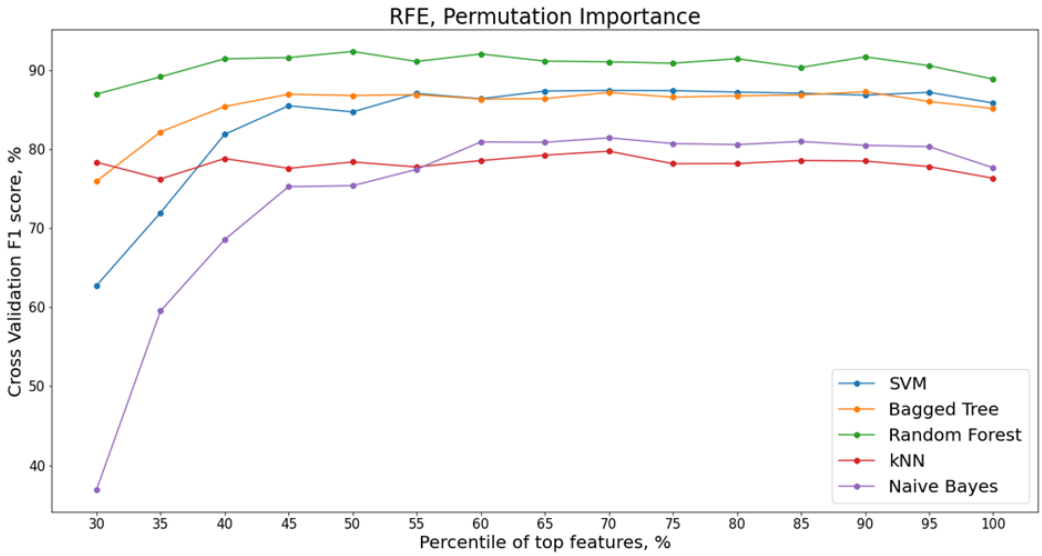


Figure 26. Recursive Feature Elimination (RFE) for varying percentiles of decorrelated feature set, ranked by permutation importance, Z24 dataset

4. Implementation

4.1 Context

UCD worked closely with Irish Rail to carry out implementation in Irish Rail assets and ensure that despite Covid19 related challenges, translation of WP5 work, its implementation in full scale and integration with WP7 are established. To this extent, existing data from a pilot study on an instrumented train over a well known accident and its repair in Ireland are considered. This was subsequently followed up with a full test on a scour impacted bridge.These two examples clearly demonstrate not only how damage may be detected related to hazards, but also how repair can also be assessed. These methods can be adapted to other networks and application areas as well.

4.2 Malahide Viaduct Example

In 2009, two spans and one pier foundation of the Malahide Railway Viaduct were replaced with stiffer elements after a scour induced collapse. Six years later, a pilot test with an instrumented carriage collected train vibration data as the vehicle travelled repeatedly over the viaduct on the Dublin-Belfast railway track. This pilot data is first used for assessment and full scale implementation possibility, extending the numerical and laboratory experiments. Figure 27 presents the location of the bridge. The Malahide Viaduct was constructed in 1844 over the Broadmeadow Estuary, Dublin, Ireland, to serve the double railway track between Dublin and Belfast. The viaduct has been rebuilt a few times over the years due to erosion/deterioration and necessary strengthening required by heavier trains. The last intervention at the bridge took place in late 2009 after two spans and one pier collapsed due to bridge scour. The replaced span beams are considerably stiffer than those of other spans and the new pier foundations with micropiles can be assumed to be stiffer than the timber piled foundations of the other piers.

Figure 27. Location of Malahide Viaduct

The current structure (Figure 28) is almost 175m and consists of 12 spans. The total width is ~9.0 m. The inner spans (Spans 3 – 10) consist of 15.85 m precast concrete beams while the two end spans, also made from precast concrete, are 12.2 m. The beams rest on cut stone masonry piers. The new pier (Pier 4) is made from in-situ reinforced concrete with a precast bearing shelf.

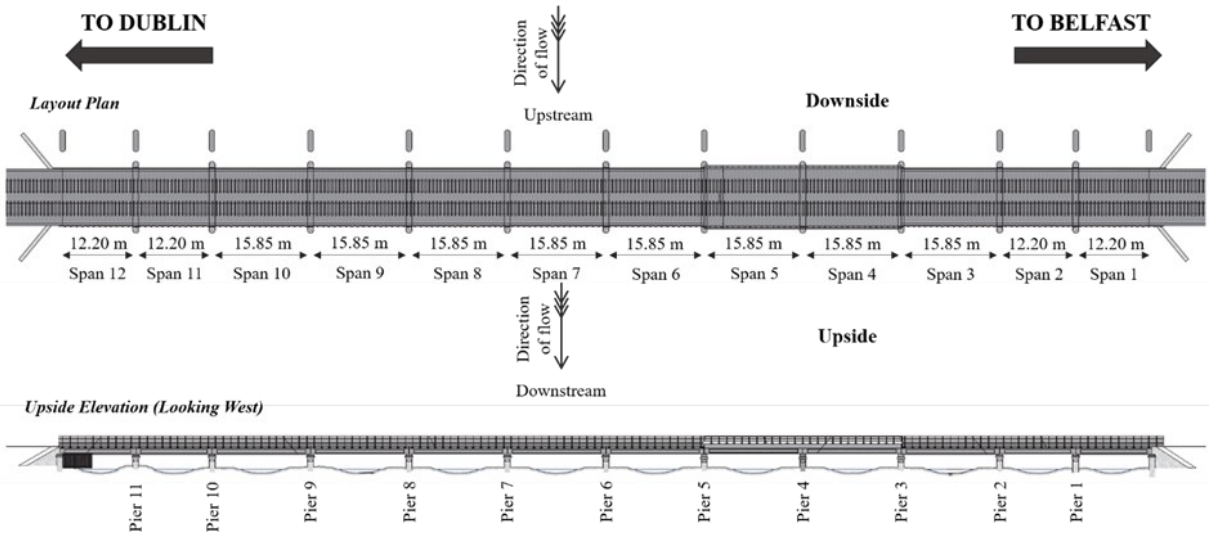


Figure 28. Plan & elevation of the Malahide Viaduct

The data was obtained from a previous pilot study of the leading carriage of a 5-carriage train set which was instrumented with multiple accelerometers to record the vibration response of the in-service vehicle. The measurement system was installed on the leading bogie. The available data was over a 5-week period in 2016. Only the vertical acceleration data of the bogie collected on the train travelling from Dublin to Belfast is investigated. The velocities of the train vary in the range, 85 km/h – 120 km/h and increase as the train crosses the bridge. A sample of the vertical acceleration signal of the bogie is shown in Figure 29. A 6th order Butterworth lowpass filter with a cut-off frequency of 15 Hz was applied to filter the data and the filtered signal is displayed. The acceleration amplitudes recorded on Spans 4 and 5 appears to be less than that of the rest of the bridge. This is assumed to be due to stiffer structure in this location.

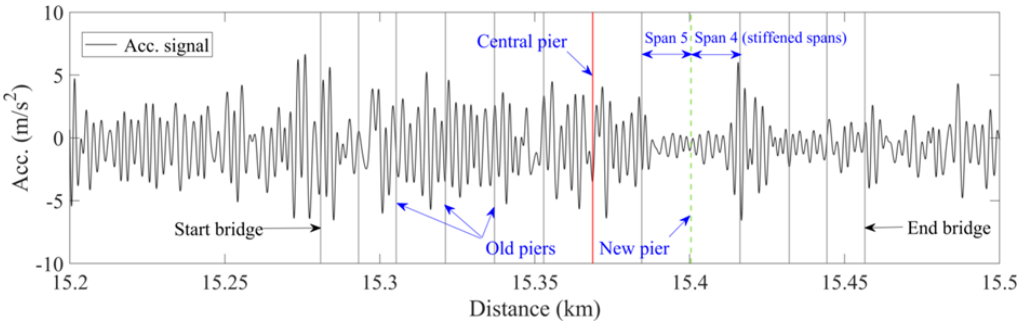


Figure 29. Sample vertical acceleration of a bogie

A scalogram (Figure 30) shows the signal for the train on the bridge and on the track before/after it. There is less vibration in the stiffened spans, particularly for the dominant frequencies. It is acknowledged that a second region of low vibration is evident towards the end of the bridge, where the spans have not been stiffened.

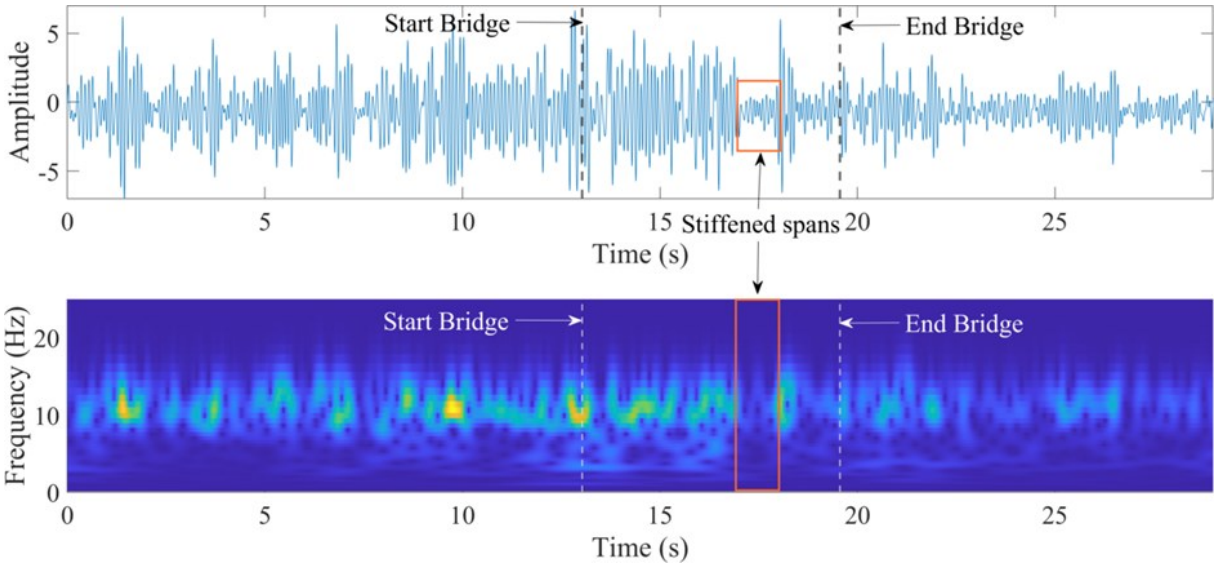
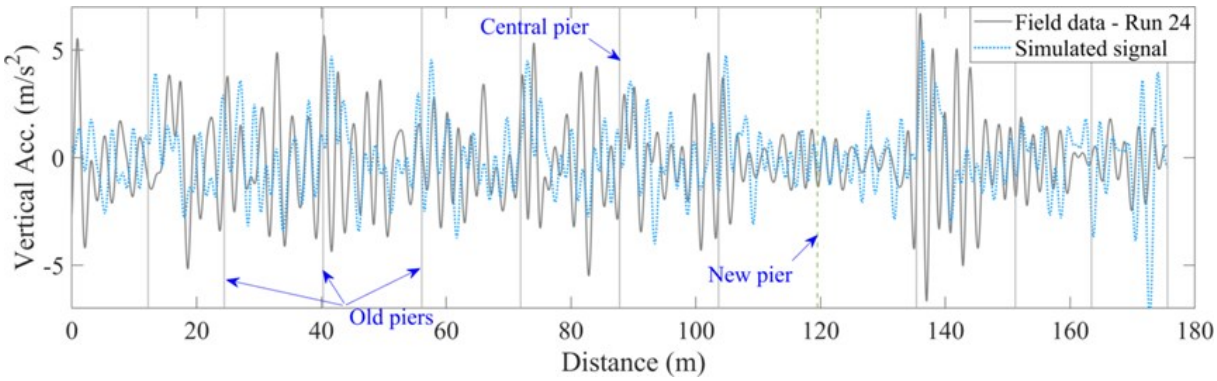


Figure 30. Acceleration responses of a train on a bridge and related scalogram

A model of the train bridge interaction was subsequently developed and a parameter study led to a reasonable match with the model with the experiments, which further led to estimates of impact of various parameters on the system. The dashed blue curve in Figure 31 depicts the signal obtained from the numerical model. The velocity of the train was set at a constant value of 103.6 km/h in the model.

This represents the average velocity recorded for. The measured acceleration for this particular run is plotted as the solid (black) curve and is used as the benchmark. The simulated signal across the new pier and spans correlates well with the field measurements.

In addition, at the other piers, there is a good match between the simulated and measured field signal. It acts as a stable reference and is considered to correspond well to the field examples.



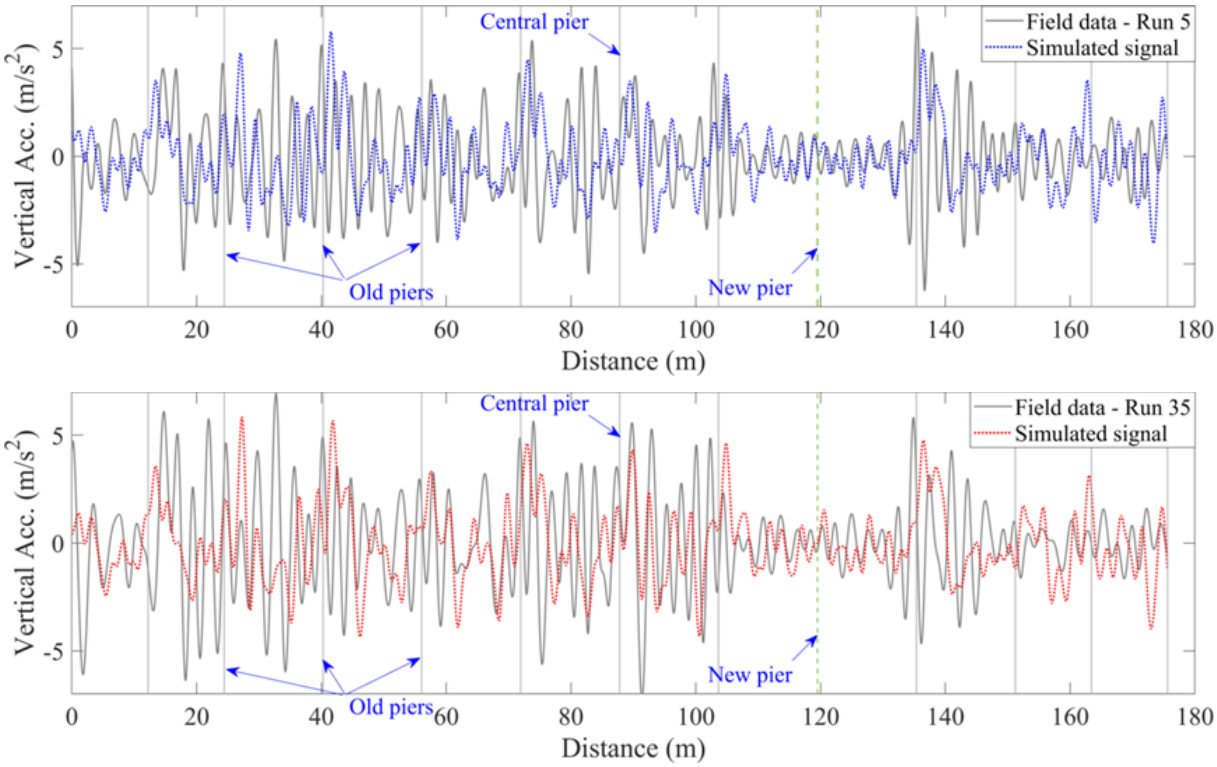


Figure 31. Examples of model-based comparison of field measurements and subsequent establishment of baseline signal

A 25 m section of the bridge is illustrated in Figure 32 including the entire stiffened Span 5 and partial sections of Spans 4 and 6 to investigate variations of speed, representative of testing ranges. The variations in the signal due to velocity are significant at about 100 m and 110 m distance along the bridge, as well as around the piers. The differences in the measured signal are clearly more significant and are not simply the result of small velocity differences.

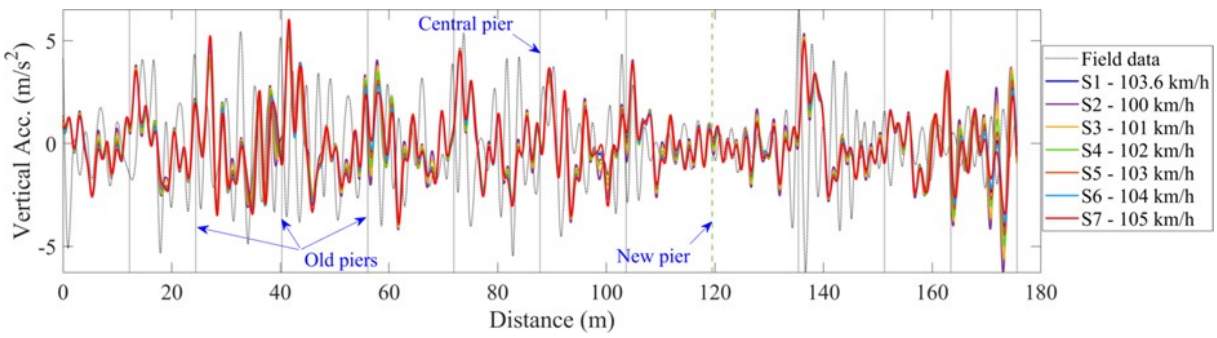


Figure 32. Model based estimates of effects of changes in velocity and comparison with field measurements

4.3 Scour Repair Assessment

Within Irish Rail network, the scour repair assessment of UBE30 bridge was taken up next for implementation. This also is representative of one of the SIRMA hazards.

The bridge is located in County Clare, Ireland, over the River Robe (Figure 33). UBE30 has a single span of 4.5 m length and serves a single railway line between Limerick City and Sixmilebridge City.

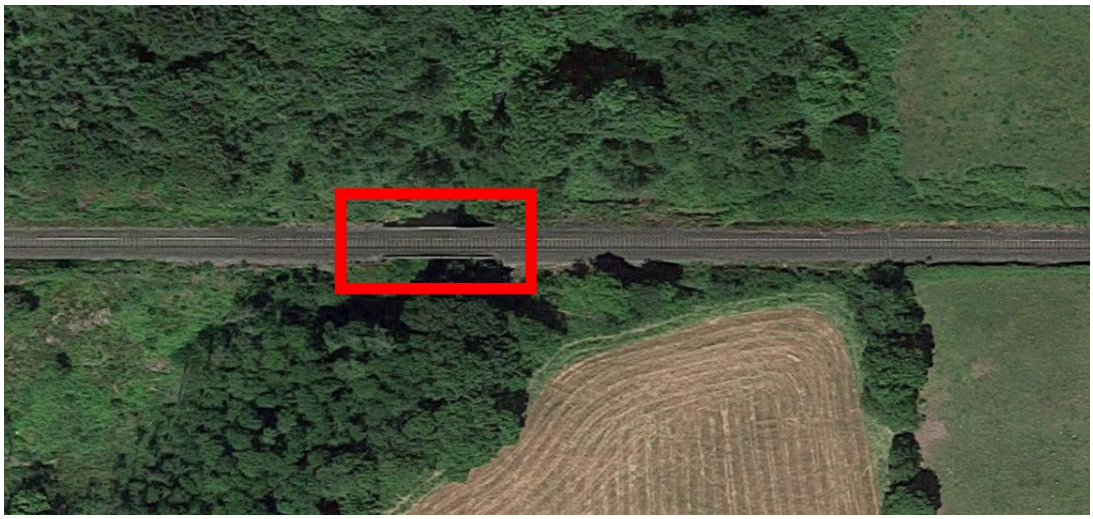


Figure 33. Location of UBE30 bridge in Ireland undergoing scour repairs

The superstructure consists of precast concrete beams supported by masonry and concrete abutments. A photograph of the bridge before repair is presented in Figure 34. It can be observed that the site was already prepared/equipped for the repair works.

Figure 34. UBE30 bridge in Ireland before and after scour repairs

Scour defects were identified along the west abutment and the repair works are presented in Figure 35. A 80 cm wide concrete encase-ment was the repair solution adopted for this bridge. Six wireless accelerometers were used to collect abutment acceleration data in a synchronized manner with measurement range +/1 10g, accuracy 10mg, resolution 12 bit, sampling frequency 128Hz (Figure 36). Each abutment was instrumented with three sensors installed on the concrete surface). Accelerometers S1, S2 and S3 were installed on the west abutment at approximately 1 m apart and approximately 1.8 m from the edges of the abutment at a height of 2.5 m. A similar attempt was made to keep these proportions on the east abutment

for S4, S5 and S6, but small variabilities existed due to accessibility at the abutment concrete surface.

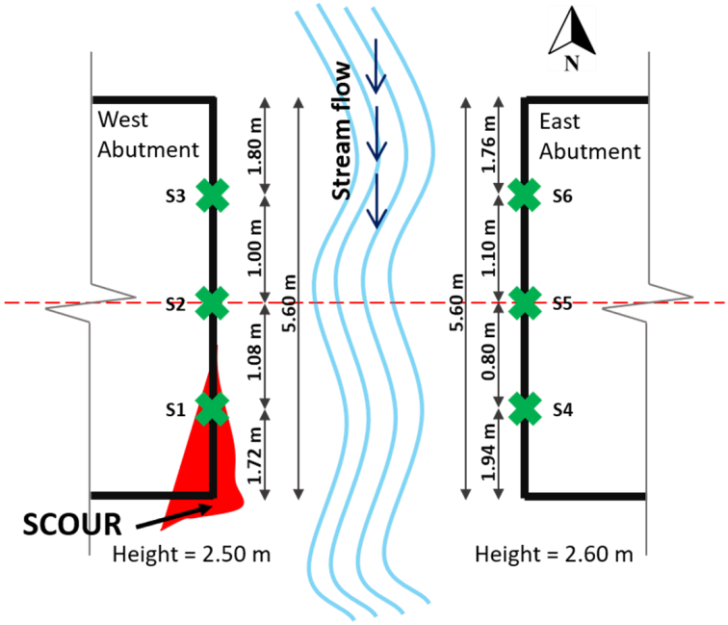


Figure 35. Sensor (accelerometers) placement on UBE30 for detecting changes due to before and after scour repair

Figure 36. Photographs of Sensor (accelerometers) placement two abutments

Accelerations induced by five passing trains were collected at different frequencies. Data produced by Train 3, travelling from Sixmilebridge to Limerick, is presented (Figure 37) for all six sensors. Train 3, which is a 2-carriage train, needs approximately 2 seconds to cross the bridge. Data were collected two weeks apart before and after the repair works were performed.

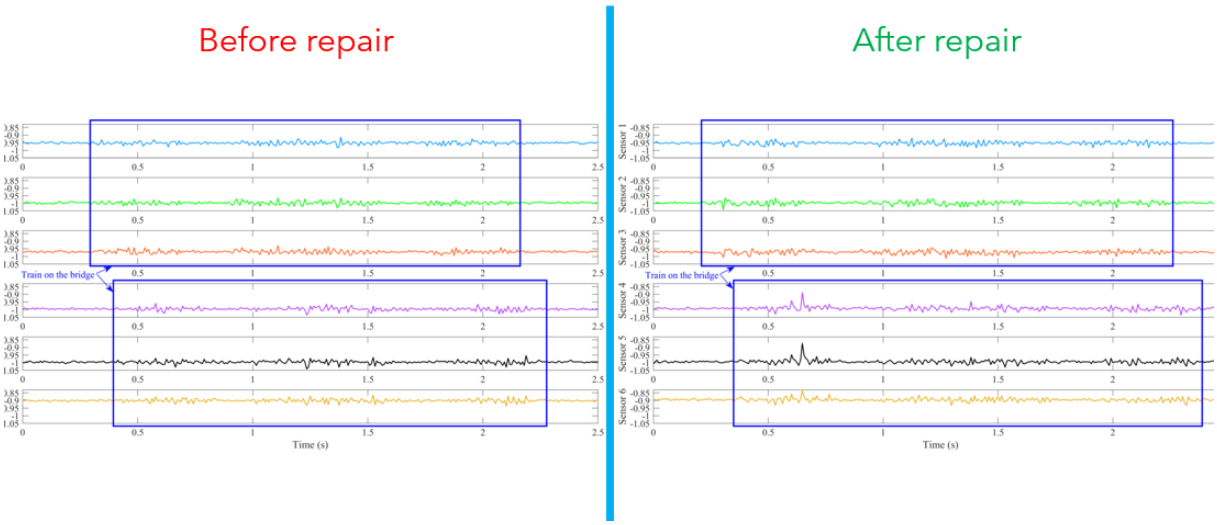


Figure 37. Acceleration responses recorded in sensors before and after repair

Data analysis was carried out in both frequency and time domains, looking into various ways of measurement analyses and also indicators of features of interest. This is in line with the previous sections of this report as well as with report D5.3.

The measured acceleration data is analysed firstly in the frequency domain to assess changes in the dynamic parameters of the bridge before and after the scour repair. Traditional vibration-based scour detection techniques analyses bridge modal parameters, such as natural frequencies, mode shapes and damping. Since damping estimates are more variable, methods based on natural frequency and mode shape have received more attention for scour detection techniques. The bridge natural frequencies tend to reduce due to scour due to the change of boundary conditions but this change may get influenced by a shape of the scour hole (symmetrical/unsymmetrical), and the non-linear behaviour of soil underneath the founda-tion. For this reason, bridge Operating Deflection Shapes (ODS) and mode shapes were used for analysing the data in the frequency domain and Mahalanobis distances between each sensor's result before and after scour repair were assessed.

Due to simplicity and ease of execution with reasonable results, Frequency Domain Decomposition (FDD) technique is used to extract first mode shape of the bridge abutments from the measured accelerations. FDD is a peak-picking technique that uses singular value decomposition of the spectral density matrix for each frequency of the response . The singular vectors obtained using the FDD technique provide the mode shape amplitudes corresponding to a selected frequency.

For time domain analyses, Principal Component Analysis (PCA) was chosen due to its ability of dimensionality reduction and sensitivity to changes due to environment and structural damage. PCA is the orthogonal projection of the data onto a lower dimensional space, (principal subspace) so that the variance of the projected data is maximized. On reducing the complex data set to a lower dimension, PCA reveals some simplified structures relevant to the data set which can be extracted using eigenvalue decomposition on the sample covariance matrix.

Here the output acceleration responses are taken for PCA and from the principal subspace, the principal com-ponents (PCs) that explain more than 90% of the variance are considered. Mahalanobis distance applied on the PCs are shown to distinguish the rehabilitation stage from the degraded system state.

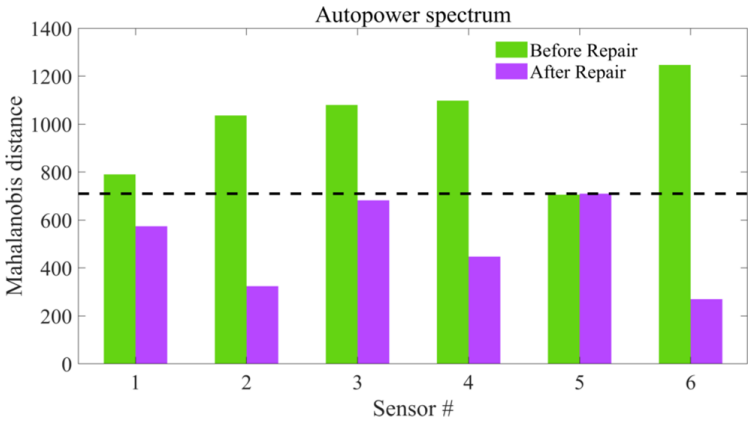


Figure 38. Auto Power Spectrum estimates for before and after repair

For the analysis of the in the frequency domain, Auto Power Spectrum (APS) based operational deflected shapes (ODS) and the first mode shape were calculated from bridge accelerations due to traversing Train 3 before and after the scour repair work. The principal components (PC) of the measured parameters for each sensor are calculated which are then used to obtain the values of Mahalanobis distance between PC of each sensor and all other sensors. The average value of Mahalanobis distance from each sensor is compared before and after the scour repair. The results of the Mahalanobis distances from each sensor APS before and after scour repair are shown in Figure 38. Similarly, the results using first mode shape amplitudes from each sensor before and after scour repair are shown in Figure 39.

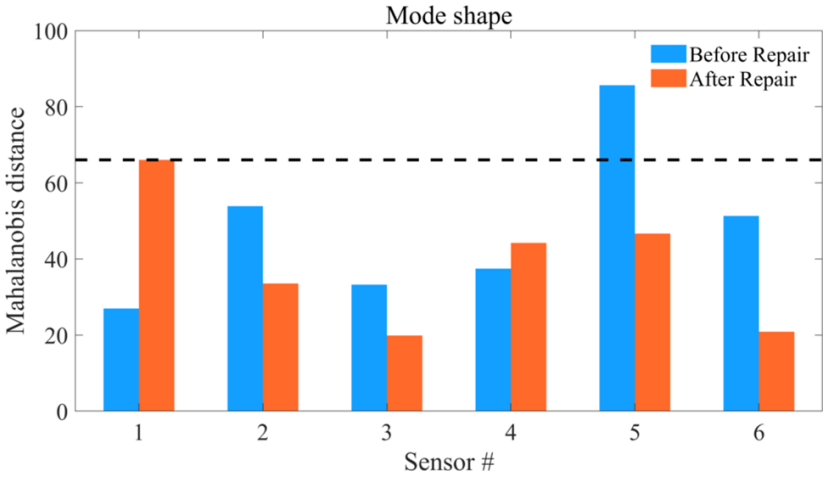


Figure 39. Modeshape based estimates with Mahalanobis distance as a marker for before and after repair

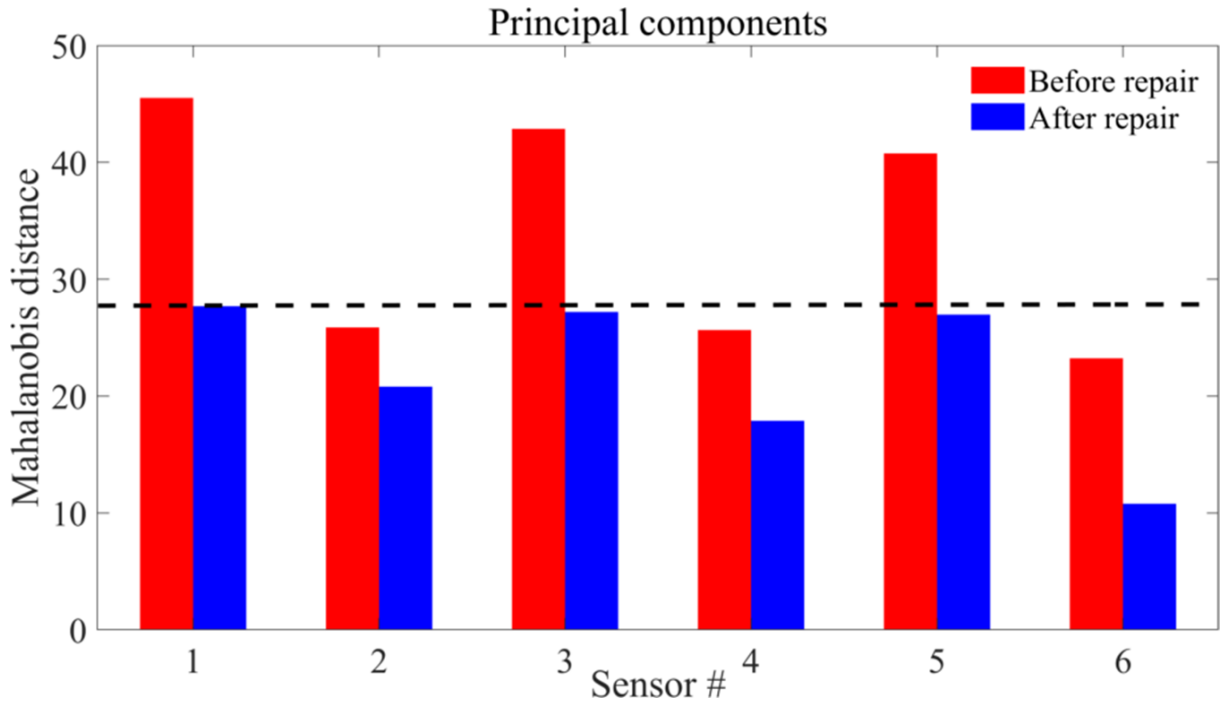


Figure 40. A Principal Component Analysis based time domain estimates with Mahalanobis distance as a marker for before and after repair

In order to provide a clearer understanding of the time domain analysis, the acceleration signals obtained from the sensors are first transformed to an orthogonal space using PCA. This reduced order model now contains the PCs which by themselves are inadequate to identify the pre and post repair stage of the bridge. The use of Mahalanobis distance as the damage indicator between the sensor PCs provide exact information before and after repairs. Figure 40 clearly presents the Mahalanobis distance features before and after the scour repairs. It is evident that time domain methods are equally efficient at determining the monitored state of a system. A real-time approach is possible but it can be more complex. Moreover, there is less need in this case for a real-time detection.

4.4 Further Application in Irish Rail Network

The Irish Rail network, even though small has significant assets. For scour, there are already several bridges which are affected and such instrumentation and monitoring can be of great use.

Similarly, there are other hazards like flooding, for which extensive inspection are often needed and instrumentation like this can help in assessing the condition of vulnerable structures.

Old bridges requiring loading restrictions, detection of soft spots along rails and assessment of repairs are also aspects where such applications can be useful.

Overall, good instrumentation and measurement can often save time and money, while maximising safety and serviceability.

It also allows for an extensive evidence base for decision making on railway infrastructure assets.

This report summarises the work that supports the repository along with representative results. All data and codes are available on request. The applications and implementations use real examples from infrastructure and consequently it has been made as open as necessary but as closed as needed.

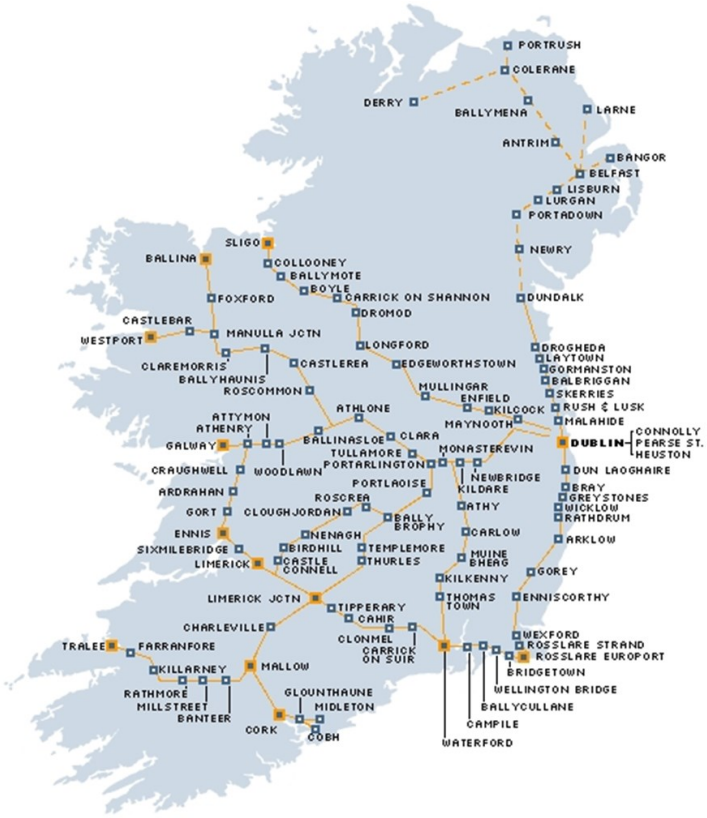


Figure 41. The Irish Rail Network

See further in:

Micu, E. A., Khan, M. A., Bhowmik, B., Florez, M. C., Obrien, E., Bowe, C., & Pakrashi, V. (2021, August). Scour Repair of Bridges Through Vibration Monitoring and Related Challenges. In *International Conference of the European Association on Quality Control of Bridges and Structures* (pp. 499-508). Springer, Cham.

Micu, E. Alexandra, Eugene J. OBrien, Cathal Bowe, Paul Fitzgerald, and Vikram Pakrashi. "Bridge damage and repair detection using an instrumented train." *Journal of Bridge Engineering* 27, no. 3 (2022): 05021018.

Acknowledgements

This report was carried out in the framework of the Strengthening the Territory's Resilience to Risks of Natural, Climate and Human Origin (SIRMA) project, which is co-financed by the European Regional Development Fund (ERDF) through INTERREG Atlantic Area Programme with application code: EAPA_826/2018.

The sole responsibility for the content of this publication lies with the authors. It does not necessarily reflect the opinion of the European Union. Neither the INTERREG Europe programme authorities are responsible for any use that may be made of the information contained therein.

References

Basuraj, et al. Damping estimation of a pedestrian footbridge–an enhanced frequency-domain automated approach. Journal of Vibroengineering 23.1 (2021): 14-25.

Bhowmik, B., Tripura, T., Hazra, B. and Pakrashi, V., 2020. Real time structural modal identification using recursive canonical correlation analysis and application towards online structural damage detection. Journal of Sound and Vibration, 468, p.115101.

Bhowmik B, Tripura T, Hazra B and Pakrashi V. (2020). Robust linear and nonlinear structural damage detection using recursive canonical correlation analysis. Mechanical Systems and Signal Processing, 136,106499.

Mucchielli P, Bhowmik B, Hazra B and Pakrashi V. (2020). Higher-order stabilised perturbation for recursive eigen-decomposition estimation.

Bhowmik, B., Panda, S., Hazra, B. and Pakrashi, V., 2021. Feedback-driven error-corrected single-sensor analytics for real-time condition monitoring. International Journal of Mechanical Sciences, p.106898.

Bhowmik, Basuraj, Budhaditya Hazra, and Vikram Pakrashi. Real-Time Structural Health Monitoring of Vibrating Systems. CRC Press, 2022.

Bhowmik, B., Tripura, T., Hazra, B., & Pakrashi, V. (2019). First-order eigen-perturbation techniques for real-time damage detection of vibrating systems: Theory and applications. Applied Mechanics Reviews, 71(6).

O'Donnell D, Wright R, O'Byrne M, Sadhu A, Edwards Murphy F, Cahill P, Kelliher D, Ghosh B, Schoefs F, Mathewson A, Popovici E and Pakrashi V. (2017). Modelling and Testing of a Historic Steel Suspension Footbridge in Ireland. Proceedings of the ICE, Bridge Engineering, 170 BE2, 116-132

Pakrashi V, Harkin J, Kelly J, Farrell A, and Nanukuttan S. (2013). Monitoring and Repair of an Impact Damaged Prestressed Concrete Bridge, Proceedings of the Institute of Civil Engineers, Journal of Bridge Engineering, 166(1), 16-29.

Buckley B, Ghosh B and Pakrashi V. (2021). A Dynamic Harmonic Regression Approach for Bridge Structural Health Monitoring. Structural Health Monitoring, https://doi.org/10.1177/1475921720981735

Buckley, Tadhg, Bidisha Ghosh, and Vikram Pakrashi. "A Feature Extraction & Selection Benchmark for Structural Health Monitoring." Structural Health Monitoring (2022): 14759217221111141.

Maeck, J., De Roeck, G., (2003). Description of Z24 benchmark. Mech. Syst. Signal Process. 17, 127–131. https://doi.org/10.1006/mssp.2002.1548

Peeters, B., Software, S.I., Roeck, G. De, (2000). One Year Monitoring Of The Z24-Bridge : Environmental Influences Versus Damage Events Status of the paper B . P EETERS AND G . D E R OECK . One year monitoring of the z24-bridge : environmental.

Micu, E. A., Khan, M. A., Bhowmik, B., Florez, M. C., Obrien, E., Bowe, C., & Pakrashi, V. (2021, August). Scour Repair of Bridges Through Vibration Monitoring and Related Challenges. In *International Conference of the European Association on Quality Control of Bridges and Structures* (pp. 499-508). Springer, Cham.

Micu, E. Alexandra, Eugene J. OBrien, Cathal Bowe, Paul Fitzgerald, and Vikram Pakrashi. "Bridge damage and repair detection using an instrumented train." *Journal of Bridge Engineering* 27, no. 3 (2022): 05021018.