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# Temperature-based Damage Detection for the Commissioning Dataset of the MX3D Bridge

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**Abstract.** Environmental and operational variations (EOV) remain a major obstacle for the successful transfer of structural health monitoring (SHM) techniques from laboratory experiments to full-scale structures. With evidence that timely interventions significantly increase the service-life and reduce the overall life-cycle cost of ageing infrastructure, carrying out SHM in the presence of EOV is therefore of high priority within the civil engineering community.

The temperature-based measurement-interpretation (TB-MI) approach monitors the thermal response of an instrumented structure and detects changes linked to damage by minimising the impact that temperature variations have on anomaly detection techniques. An iterative regression-based thermal response prediction (IRBTRP) methodology is utilised in the TB-MI approach, and is trained on the healthy condition of the structure to predict its response to temperature fluctuations. The difference between the measured and predicted response provides temperature-corrected signals that are used for damage detection.

The TB-MI approach and the IRBTRP methodology are applied to detect damage on the MX3D Bridge, the world's first structure produced through metal additive manufacturing. This study demonstrates that the TB-MI approach enables earlier and more widespread damage detection amongst multiple sensor groups, compared to when no temperature effects are considered. The adoption of the TB-MI approach can therefore greatly increase the reliability and our reliance on SHM techniques for critical infrastructure.

**Keywords:** Temperature-based structural health monitoring, Environmental and operational variability, Thermal response predictions, Anomaly detection, Data-driven methods, Metal additive manufacturing

## Introduction

The MX3D Bridge is the first structure built using metal additive manufacturing (AM), as shown in Fig 1, deposited through wire and arc additive manufacturing (WAAM). Metal produced through WAAM exhibits an anisotropic material response, due to its layer-by-layer

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deposition that reduces strength, stiffness and ductility in the build direction [1], and is still under investigation. A physics-based model that can fully capture the material and geometric variation will have significant complexity and computational cost, therefore a data-driven approach is currently deemed more reliable for the structural assessment of the MX3D Bridge.

A structural health monitoring (SHM) sensor network was installed on the bridge to study its short and long-term structural behaviour. Short-term defines the sub-year structural response. Long-term behaviour is the evolution of the short-term response due to structural change that is caused by damage (e.g. cracking) or changes in the loading and boundary conditions (e.g. support settlement) [2]. As the first metal structure built using AM, the long-term response of the MX3D Bridge is currently unknown and should be researched using data-driven SHM methodologies.


**Fig. 1**. The MX3D Bridge during the commissioning period at the University of Twente.

Environmental and operational variability (EOV, e.g. temperature, traffic loading) is known to mask valuable structural response changes linked to damage [3], [4]. SHM techniques have been extensively applied to laboratory experiments, however EOV has affected their application to real-world conditions [5], [6]. Significant research has been carried out in minimising the effect of temperature variations in data-driven SHM techniques [7], such as temperature effect filtering for vibration-based methods [8], [9] and thermal response prediction methodologies [10], amongst other approaches [11]–[14], for static-based techniques. To monitor the long-term performance, it is better to study the evolution of temperature-induced responses rather than removing temperature effects [7]. A temperature-based measurement interpretation (TB-MI) approach to damage detection therefore applies anomaly detection techniques to signals of the difference between the measured structural response and predicted thermal response. An iterative regression-based thermal response prediction (IRBTRP) methodology [15] was developed to improve thermal response predictions and enable widespread application to civil infrastructure, and includes data preparation and an automatic selection of the customisable parameters (i.e. the hyperparameters).

This study applies the IRBTRP methodology as part of the TB-MI approach to remove the effects of pedestrian loading and to predict the healthy thermal response of the MX3D Bridge to temperature variations over a 2-month commissioning dataset, presenting a subset of the work available in [16]. Anomaly detection techniques are subsequently used to evaluate the application of this methodology in a real-world scenario.

## 1. Measurement Interpretation Methodologies for Damage Detection

The response-only and the TB-MI approaches are described in Fig. 2, along with the anomaly detection techniques that are used for detecting damage. The response-only approach interprets structural measurements that have been minimally pre-processed (see the dashed lines in Fig. 2), whilst the TB-MI approach is hereby detailed.

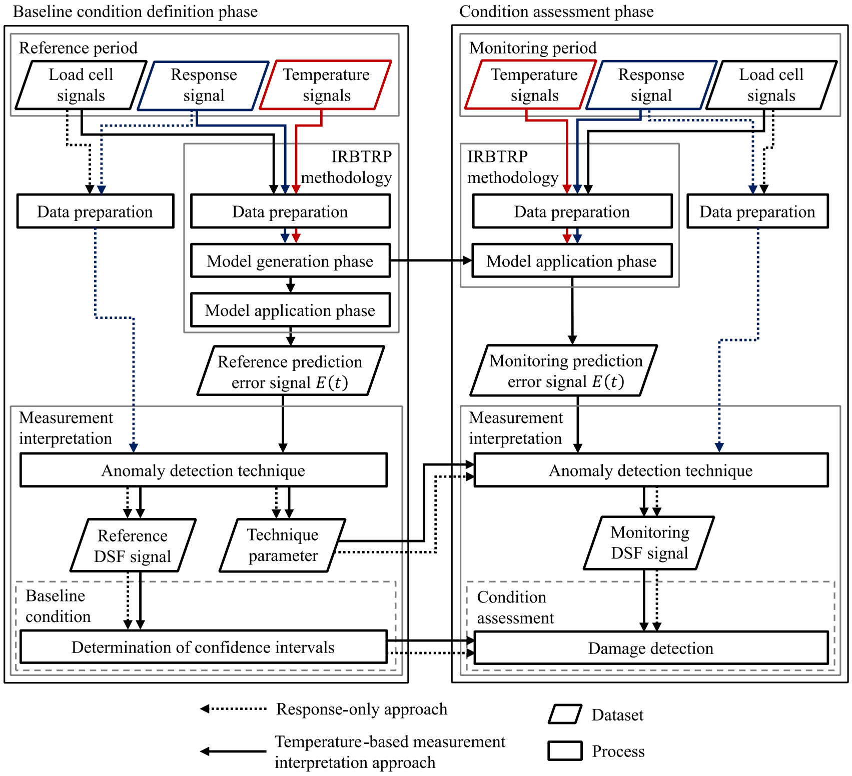


**Fig. 2.** Flowchart of the response-only and TB-MI approaches for damage detection [16].

## *1.1 The TB-MI Approach*

The TB-MI approach is applied to infrastructure instrumented with temperature sensors to measure its distributed thermal profile and uses regression methodologies, such as the IRBTRP methodology that is outlined herein, to characterise and remove the temperature-driven structural response before further analysis, as shown by the solid lines in Fig. 2.

### *1.1.1 The IRBTRP Methodology*

The IRBTRP methodology was developed to accurately predict the thermal response of a structure to enable both a detailed understanding of its operational response and an improved application of damage detection techniques [15] (see its high-level steps in Fig. 2). For the baseline condition definition phase of the TB-MI approach, a reference period that corresponds to the baseline (e.g. healthy) state of the structure is utilised and divided into training, validation and testing subperiods for regression model generation, validation and evaluation, respectively.

An initial data preparation stage removes the influence of traffic loading and high-frequency noise to produce a dataset with only the distributed temperature and thermal response. The subsequent model generation phase is applied to the temperature signals and a single response signal (i.e. one regression model per sensor). Hyperparameters (i.e. customisable parameters relating to measurement pre-processing, regression and prediction post-processing) and regression algorithms are used within the IRBTRP methodology for adapting and optimising (through a grid-search) the methodology to its application. To improve predictions and reduce computational cost, a hyperparameter specification stage determines the values that are computed in the grid-search by using their observed effect on initial predictions for a representative subset of the sensor network. The optimal regression model (i.e. the combination of tuned hyperparameters and the trained regression algorithm) is the one that provides the least validation set error.

The unseen testing subperiod data is used to evaluate the regression model within a model application phase. The prediction error signal $E(t)$ is the difference between the measured $M(t)$ (after data preparation) and predicted $P(t)$ response signals. The accuracy of the regression model $e_{\mathrm{p}}$ is evaluated as the root-mean squared error (RMSE) using

$$e_{\mathrm{p}} = \frac{\sqrt{\frac{1}{N}\sum_{i=1}^{N} E(t_i)^2}}{r_{\mathrm{ref}}} \tag{1}$$

for $N$ recorded data points, where $r_{\mathrm{ref}}$ is the reference period range of $M(t)$. The prediction accuracy is determined for both the validation and testing subperiods as $e_{\mathrm{p,val}}$ and $e_{\mathrm{p,test}}$, respectively. For temperature-corrected analysis, the optimal regression model (i.e. the one that provides the lowest $e_{\mathrm{p,val}}$) is re-applied to predict the thermal response over the monitoring dataset.

### *1.2 Anomaly Detection Techniques*

Anomaly detection techniques are used to identify underlying changes in sensor signals, with the detected anomalies assumed to correspond to damage when all other driving-factors (e.g. EOV, sensor degradation, boundary conditions) are consistent. The inputs to the anomaly detection techniques are the measured $M(t)$ and error $E(t)$ signals for the response-only and TB-MI approaches, respectively. The signal that is outputted is a damage-sensitive feature (DSF) signal, for which confidence bounds (e.g. $\mu \pm 3\sigma$, $\mu \pm 6\sigma$, where $\mu$ and $\sigma$ are the mean and standard deviation of the reference DSF signal, respectively) are defined to characterise the baseline state of the structure (see Fig. 2). False negatives (i.e. missed damage) can occur when: (i) the sensors used to construct the DSF signal are not local to the damage; (ii) damage severity is too low; and (iii) the confidence bounds are too large.

A condition assessment phase (see Fig. 2) utilises the monitoring dataset and determines the current state of the structure based on whether the computed DSF signal is within the predetermined confidence interval (i.e. inside and healthy, or outside and damaged). In this study, the anomaly detection techniques that are applied to the signals of sensor clusters (i.e. groups of sensors) are moving principal component analysis (MPCA) [17] and cointegration [18].

## 2. The MX3D Bridge

The world's first structure constructed using metal AM is shown in its Twente location in Fig. 1. The bridge's hollow handrails, substructure, and decorative end swirls were separately printed by MX3D, and hand welded along with the conventionally-made deck plate and two rectangular hollow section end beams. The bridge is fitted with a comprehensive sensor network, with the data from strain gauges (denoted by SG*XX*, where *XX* is the sensor number) and thermistors (T*XX*) used in this study. The locations of the substructure sensors in this study are displayed in Fig. 3. Additional information on the MX3D Bridge manufacturing process and dimensions can be found in [16].

A 2-month dataset was collected during the sensor network commissioning period at the University of Twente, with temperature being the dominant source of EOV for the MX3D Bridge. Typical commissioning period responses measured by strain gauges are provided in Fig. 4 for a 3-day period, along with temperature measurements. The baseline of SG04 and SG13 signals show a daily variation that strongly correlates with thermistor T06's output.

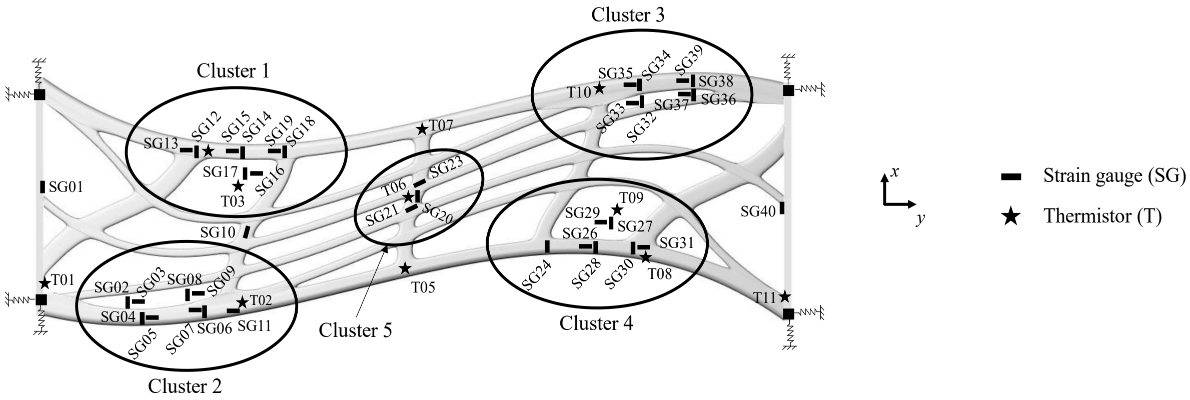


**Fig. 3**. Locations of strain gauges and thermistors on the MX3D Bridge substructure and of the sensor Clusters 1-5 used for anomaly detection.

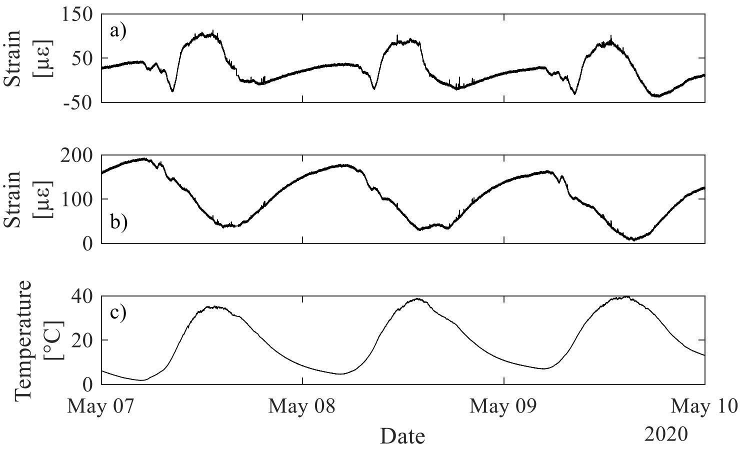


**Fig. 4**. Typical measured response for a) SG04 strain gauge, b) SG13 strain gauge and c) T06 thermistor over 3 days of the MX3D Bridge commissioning dataset.

## 3. Application of the Measurement Interpretation Approaches to the MX3D Bridge

The response-only and TB-MI approaches are applied to the commissioning dataset of the MX3D Bridge to detect the presence of simulated damage. The IRBTRP methodology is used to predict the thermal response measured by the bridge strain gauges, and is outlined in Section 3.1 with damage detection reported in Section 3.2.

### *3.1 Temperature Modelling*

The first step of the methodology involves data preparation of the input signals that provides structural response signals free from operational variations. The hyperparameter specification is undertaken for all of the hyperparameters using a representative subset of sensors, however the selection process is omitted in this paper but can be found in [16]. The resulting grid-search computes 176,960 combinations of the hyperparameters and regression algorithms for each of the 70 sensor signals on the MX3D Bridge [16].

### *3.1.2 Thermal Response Predictions*

Following the grid-search computation of all hyperparameter and regression algorithm combinations, the optimal regression models for all sensors are selected. The average validation and testing errors for all the MX3D Bridge sensors are of $e_{\mathrm{p,val}} = 1.2\%$ and $e_{\mathrm{p,test}} = 6.2\%$, demonstrating an overall good accuracy of the thermal response predictions provided by the IRBTRP methodology. The significant differences between the validation and testing error are found to be related to new temperature conditions unseen during training, as detailed in [16], which highlights the importance of including all EOV conditions within the model generation phase. The measured and predicted signals for SG04, SG13 and SG27 strain gauges (with $e_{\mathrm{p,test}}$ of 4.1%, 3.5% and 3.4%, respectively) are presented in Fig. 5 for an unseen 5-day period of the testing dataset. The variations in the strain response of the bridge measured by the three sensors linked to both daily and hourly temperature fluctuations (see May 27 in Fig. 5) are clearly well predicted.

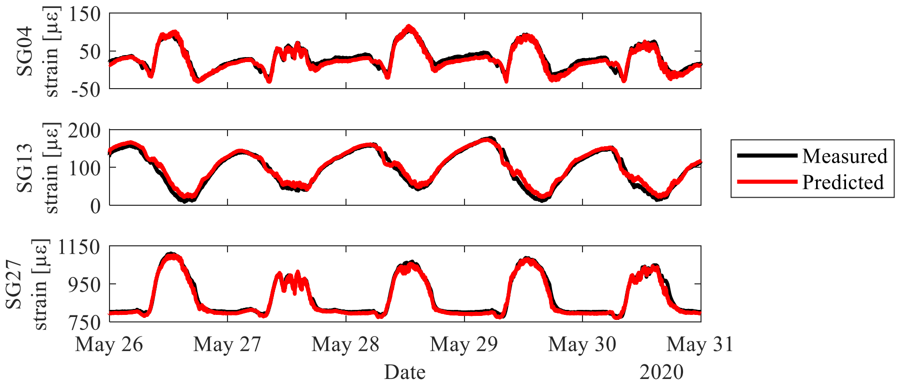


**Fig. 5.** Measured and predicted thermal response of SG04, SG13 and SG27 strain gauges for 5 days of the unseen testing period of the MX3D Bridge.

### *3.2 Detection of Simulated Damage*

The decorative end swirls on the MX3D Bridge were removed close to the end of the commissioning period, providing sensor measurements during a period of structural change. Deliberate physical damage could not occur prior to placement in Amsterdam, the Netherlands, due to the high-profile nature of the structure. The anomaly detection techniques of MPCA and cointegration are both evaluated using response-only and TB-MI approaches to determine their influence on the ability of the anomaly detection techniques to identify the damage simulated by the end swirl removal. The MX3D Bridge strain gauges are assigned to six clusters, as shown in Fig. 3 for Clusters 1-5 and in Table 1 for Clusters 1-6.

The reference period used for the baseline condition definition phase is the same as that used for the prior IRBTRP methodology. A 2-week long moving window is adopted for MPCA, as previous studies have recommended a window that is substantially larger than the

**Table 1**. Summary of the sensor clusters and damage detection for the response-only and TB-MI approaches.

| **Cluster** | **Strain gauges** | **Approach** | **Anomaly detection** | |
|---|---|---|---|---|
| | | | **MPCA** | **Cointegration** |
| 1 | SG12-19 | Response-only | No | No |
| | | TB-MI | Yes | Yes |
| 2 | SG02-14, 17-19 | Response-only | No | No |
| | | TB-MI | No | No |
| 3 | SG32-39 | Response-only | No | No |
| | | TB-MI | Yes | Yes |
| 4 | SG24, SG26-30 | Response-only | No | No |
| | | TB-MI | Yes | No |
| 5 | SG20, 21, 23 | Response-only | Yes | No |
| | | TB-MI | Yes | No |
| 6 | SG01, 04, 06, 12, 14, 27, 28, 32, 34, 40 | Response-only | Yes | Yes |
| | | TB-MI | Yes | Yes |
| Detection rates | | Response-only | 33% | 17% |
| | | TB-MI | 83% | 67% |

observed daily temperature cycles [17]. Confidence intervals of $\mu \pm 6\sigma$ and $\mu \pm 3\sigma$ are adopted for MPCA and cointegration, respectively, as used in previous damage detection studies [18], [19]. The damage detection rates for all clusters using MPCA and cointegration for the response-only and TB-MI approaches are presented in Table 1, and report a 50% increase in the number of clusters detecting damage for MPCA and cointegration. For both anomaly detection techniques applied to Clusters 1, 3 and 4, the TB-MI approach enables damage detection compared to the response-only approach, which is very apparent in Fig. 6 for Cluster 1.

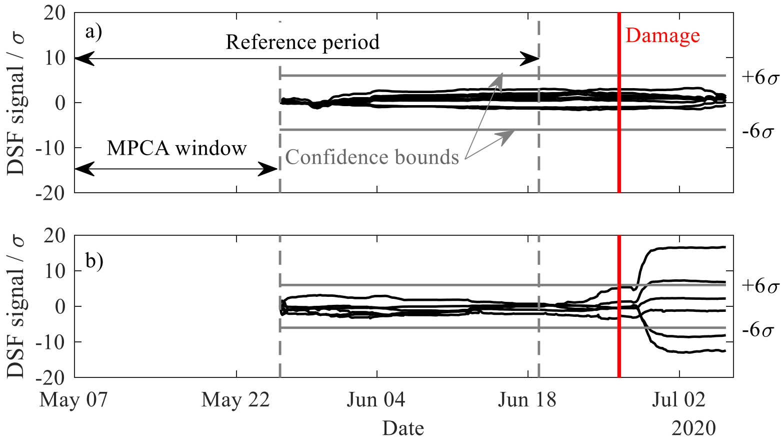


**Fig. 6.** Normalised DSF signals obtained using MPCA for the a) response-only and b) TB-MI approach for Cluster 1.

## Conclusion

The IRBTRP methodology was utilised on the MX3D Bridge to provide accurate thermal response predictions over unseen periods for testing and monitoring purposes. Error differences between the validation and testing datasets highlights the necessity of including all environmental conditions within the training dataset. Towards the end of the commissioning period, the end swirls on the structure were removed and this is used as a proxy for structural damage to the MX3D Bridge. A TB-MI approach that uses temperature-corrected structural signals is compared to a response-only approach, which applies minimal processing, and demonstrates a significantly higher rate of damage detection across multiple groups of sensors. This study demonstrates the need for structural thermal response monitoring techniques, such as the IRBTRP methodology, to overcome measurement noise, outliers, and EOV and to enable early damage detection in real-world scenarios.

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