Initial investigations into the thermal response of the first metal 3D printed bridge

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ABSTRACT: 3D printing, more formally called additive manufacturing, has the potential to revolutionise the construction sector through improved structural efficiency, reduced material use and greater architectural freedom. The first metal 3D printed structure, the MX3D Bridge, has been designed, non-destructively tested and instrumented with an extensive structural health monitoring network. This network will measure the structural behaviour of the bridge, and act as a ‘living laboratory’. In its final location in the centre of Amsterdam, the Netherlands. Initial investigations into the thermal response of the bridge are presented, based on a one-month period of data collected during a nine-month sensor installation and commissioning programme at the University of Twente, the Netherlands. The regression-based thermal response prediction methodology is employed to predict the structural response from distributed temperature measurements. Although only a two-week input data period is used for the model training, the developed regression models are capable of generating accurate response predictions.

KEY WORDS: Thermal response; additive manufacturing; bridge; metal 3D printing; temperature loads; signal processing; stainless steel; wire and arc additive manufacturing

1 INTRODUCTION

3D printing, or more correctly named additive manufacturing (AM), is an increasingly popular manufacturing method in the aerospace and biomedical sectors, and is also starting to be explored within the construction industry. It offers significant advantages over more traditional formative and subtractive techniques, including geometric flexibility – leading to both greater architectural freedom and more optimised structural efficiency, customisation opportunities, reduced material use and safer construction. Wire and arc additive manufacturing (WAAM) is a metal 3D printing technique particularly suited to the construction sector, with an essentially unlimited part size, a fast deposition rate (1-10 kg/hr) and lower equipment (off-the-shelf robotic welding arm) and consumable costs (£55/kg) than other metallic printing techniques, such as powder bed fusion [1]. The first large-scale metal 3D printed structure is the MX3D Bridge, shown in Figure 1 and introduced in Section 2, and was built using WAAM. This bridge will be placed within the centre of Amsterdam, the Netherlands in the near future. Prior to final placement it has been instrumented with an extensive structural health monitoring (SHM) network to allow the short- and long-term behaviour of printed metal to be investigated. The bridge will also act as a ‘living laboratory’, allowing studies into the flow of people and how the public interact with an instrumented, novel metal 3D printed structure in the centre of a capital city to be undertaken.

Bridges are subjected to dynamic, static and quasi-static loadings. Short span bridges, such as the MX3D Bridge, can be exposed to frequent traffic (e.g. pedestrian crossings), which generate vibrations (a dynamic response) and deformations (a static response) while loads move over the structure. The third type of loading, temperature, in contrast to static and dynamic loads, is always present, therefore, governing the long-term bridge response [2-4]. Understanding bridge behaviour (or performance under a variety of loads) is very important, especially when introducing new novel construction materials and techniques, such as WAAM, and for assessing bridge conditions. Both the static and dynamic bridge responses are influenced by temperature loads [5,6], therefore the first task in long-term SHM is to characterise the bridge thermal response. It, ideally, requires densely distributed temperature measurements, which serve as an input to the regression-based thermal response prediction (RBTRP) methodology [7], which generates the relationship between the temperature and structural response.

Figure 1. The MX3D Bridge at Dutch Design Week 2018.

This paper presents initial investigations into the characterisation of the MX3D Bridge thermal response from measurements that were collected shortly after the sensor system was installed. The main purpose of characterising the bridge response is to establish baseline conditions, to which
future response measurements can be compared for condition assessment of the MX3D Bridge.

2 MX3D BRIDGE

The MX3D Bridge is the first metal 3D printed structure built and open to the general public to use and interact with. It is a 12.5 m long pedestrian bridge, with a 10.3 m span between its supports, an average width of 2.5 m and an overall mass of 7.8 tonnes, with a printed mass of 4.6 tonnes. The bridge is comprised of two printed handrails with internal stiffeners, a substructure with longitudinal and transverse printed hollow beams, a conventionally formed deck plate and two conventionally formed rectangular hollow section (RHS) end beams, as shown in Figure 2. The side profile of the bridge is an arch, rising 0.5 m between the end and midspan. The structure was built using WAAM over a 6 month period, with 1100 km of Grade 308LSi austenitic stainless steel wire used, by a team of 6-axis industrial welding robots in Amsterdam. The bridge was printed in individual pieces and then hand welded together. The bridge was constructed by MX3D, a Dutch metal 3D printing start-up; designed, analysed and tested by Arup and Imperial College London; and the sensor network design was led by Force Technology, installed by the University of Twente and part of a larger ‘Smarter Bridge’ project team including the aforementioned partners and Autodesk and the Alan Turing Institute, the latter also including the University of Edinburgh. Significant effort was devoted to destructive material and cross-section testing in London [1,8,9] and non-destructive load testing of the partially and fully completed bridge at MX3D and the University of Twente [10], as part of the safety and verification process adopted. The MX3D Bridge was first unveiled to the public under controlled conditions at Dutch Design Week 2018 in Eindhoven, the Netherlands, shown in Figure 1. The bridge is expected to be placed within the centre of Amsterdam, the Netherlands in the near future.

In Figure 3, the locations of the sensors are shown, with the sensors either placed in predefined locations or based on the predicted parameter variation from the constructed finite element model. Sensor data collected is uploaded in real-time from a local server to the Autodesk Data360 cloud service. An initial subset of the sensor network was installed prior to, and demonstrated during, Dutch Design Week 2018, however the majority of the instrumentation and wiring installation was undertaken during a nine-month period at the University of Twente. The sensor network was also checked and verified during this period, with the bridge sitting outdoors on the campus grounds exposed to the environment, as shown in Figure 4. Sensor data collected during this time period is presented and analysed in this study.

![Figure 3: Locations of sensors used in this initial investigation, a subset of the full installed sensor network.](image3)

![Figure 4: The MX3D Bridge at the University of Twente during the sensor installation and commissioning programme.](image4)
2.1.1 Load cells and bearings
The bridge rests on four elastomeric bearings, which allow small horizontal movements arising from pedestrian loading and thermal effects (i.e. expansion, contraction), at its four corners. A ring torsion load cell is installed on each bearing to measure the applied vertical loading on the structure. The selected load cells have 0.05 – 15 tonne nominal load capacity and 2.85±1% mV/V sensitivity. The LC02 load cell and associated bearing are shown in Figure 5.

![Image](load_cell.png)

Figure 5. LC02 load cell and bearing under the MX3D Bridge.

2.1.2 Strain gauges
The surface strains of specific bridge elements are measured with 40 electrical resistance foil strain gauges (120 Ω and 350 Ω). WAAM printed material has an inherent, wavy surface profile and therefore local mechanical surface smoothening was undertaken to provide a flat, smooth surface for adhering the strain gauges. Figure 6 shows example strain gauges attached to a smoothened area on the underside of the substructure.

![Image](strain_gauges.png)

Figure 6. Example strain gauges adhered to a locally smoothened surface, prior to weatherproofing.

2.1.3 Temperature sensors
The temperature monitoring network comprises of 16 Pt100 Ω resistance thermometers, with a temperature range from -50°C to 150°C. These were glued to the underside of the deck plate, outer face of the handrails (on the inside of the bridge) and on the underside of the substructure.

3 THERMAL RESPONSE CHARACTERISATION
Previous studies have confirmed that the quasi-static bridge response, which is driven by slowly applied temperature changes can be exploited for bridge condition assessment when integrated in the temperature-based measurement interpretation (TB-MI) approach [11,12]. The main component of the approach (see Figure 7) is the RBTRP methodology, which consists of regression model generation and application phases.

In the regression model generation phase a reference dataset is selected. Ideally, the reference set should contain the entire measurement range (i.e. one year of data). The data is pre-processed using an interquartile range (IQR) analysis for outliers [13] and a moving average filter for noise [7]. It is then divided into the regression model training and testing sets. The training set can, for example, consist of each nth measurement. The remaining measurements form the testing dataset. To reduce computational time temperature measurements are converted to the principal component (PC) space. The first 1/3 of PC vectors of the temperature measurements cover the variability of the original dataset and are selected for the regression model generation. Regression models are generated for each response sensor, such as a strain gauge. Multiple linear regression (MLR) and support vector regression (SVR) are reported to give comparable results [7]. MLR, however, requires significantly less time for model generation than SVR (even up to ×100). For this reason, it is better suited for large datasets than SVR, which is the case in this study. Readers can find a detailed explanation of the steps involved in the RBTRP methodology in [12], which is excluded here for brevity.

The same data pre-processing settings are also used at the regression model application phase, in which newly collected measurements are used to predict the thermal response. Residuals between the predicted and measured bridge responses form the prediction errors (PEs). Consecutive PEs form PE signals, which are analysed for anomalies that provide an indication of anomalous structural behaviour. This stage is not covered in this paper, but will be reported in the future.

![Image](rbtrp_methodology.png)

Figure 7. The temperature-based measurement interpretation approach [12].

4 MX3D BRIDGE THERMAL RESPONSE
This section delivers initial investigations into the thermal response of the MX3D Bridge. The RBTRP methodology is employed to characterise the thermal response of the bridge. Measurement time histories and their pre-processing, response predictions, and PE signal analysis are presented herein.

4.1 Measurement time histories
Temperature, strain and load measurements collected over a one-month period have been selected for this study. During the
selected monitoring period the data collection was interrupted several times due to configuration changes and sensor modifications. The longest interruption lasted a week. 1 Hz measurements were retrieved from Autodesk’s Data360 online platform for processing and analysis. Raw load and strain time histories (further referred to as signals) from representative sensors together with the deck plate temperature (measured from T03) for the chosen monitoring duration are shown in Figures 8 and 9, respectively. The response signals are set to zero at the start of the data collection period. The signals from LC03 and LC04 are similar in nature to LC01 and LC02 respectively. In contrast, the strain signals for the MX3D Bridge are not alike – almost every strain signal has a unique pattern. Selected pre-processed strain signals are shown in the next section.

4.2 Measurement pre-processing

While the bridge was sitting on the grounds of the University of Twente campus, during the sensor network commissioning phase, it was open to the public. Noticeable spikes in the load cell signals result from visitors crossing the bridge and researchers carrying out commissioning tests. For the thermal response predictions only the temperature-induced response and distributed temperature measurements are required. The measurement pre-processing workflow is follows: i) downsample the measurement set to 1/60 Hz, ii) apply a 60 minute window for the IQR analysis, and finally iii) smooth the measurement histories with a 15 minute moving average filter. Example results of three-day load, strain and temperature signals are shown in Figures 10, 11 and 12, respectively. Pre-processed load signals are free from short term load events such as pedestrian crossings. Strains are not as sensitive to pedestrian-induced interactions as the measured loads, therefore they do not have short and sharp spikes within the raw dataset, which are removed using an IQR analysis. The strain signals are, however, contaminated with measurement noise, the effects of which are removed with a moving average filter. The temperature signals are, in general, already smooth and with no outliers. Their smoothing, however, removes short temperature fluctuations, which could be caused by sudden wind chill and cloud cover.
4.3 Thermal response predictions

The dataset of the first two weeks, of the one-month dataset being considered, is set as the reference period for the generation of regression models, which includes both training and testing. The dataset after the measurement collection disruption (i.e. after 24 May) is the monitoring period. Temperature signals are converted to the PC space. The input dataset to the regression generation is composed of 1.67×10⁻³ Hz, i.e. one measurement every 10 minutes. The remaining measurements for the testing set are used for evaluation of the regression model accuracy. The accuracy is expressed using a parameter $e_p$, which is a measure of the error computed in terms of the range of the measured response (see Eq. (1)).

$$
e_p = \frac{e_s}{r_s}
$$

(1)

$e_s$ is the root mean squared error in predictions and $r_s$ is the range of measured response at sensor $s$ for the reference period.

Insignificant improvements to the prediction accuracy are noticed when the input number of PCs is more than 10 PCs. A 40-minute thermal inertia parameter is found to result in the smallest $e_p$ values. Parameters $e_p$, $e_s$ and $r$ for the reference period are given in Tables 2 and 3. The tables also contain the parameter $e_{PE}$, which is the PE parameter expressed as a percentage and is calculated as follows:

$$
e_{PE} = \frac{|PE_s|}{r_s}
$$

(2)

$PE_s$ is the PE and $r_s$ is the range of measured response at sensor $s$ for the monitoring period.

Strains are predicted more accurately than loads. Only $e_p$ for LC04 and SG38 exceeds 5% for the reference period. Example measured and predicted responses of LC02 and SG13, over a three-day period, are shown in Figures 14 and 15. The SG13 measured and predicted responses almost coincide, with very slight deviations being discernible. The LC02 predicted response deviates visibly from the measured response during periods when the temperature decreases.

Table 2. Prediction accuracy and prediction errors of load cell measurements

<table>
<thead>
<tr>
<th>Sensor</th>
<th>Reference period</th>
<th>Monitoring period</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$e_p$</td>
<td>$e_s$</td>
</tr>
<tr>
<td>LC01</td>
<td>4.6%</td>
<td>34 N</td>
</tr>
<tr>
<td>LC02</td>
<td>4.7%</td>
<td>29 N</td>
</tr>
<tr>
<td>LC03</td>
<td>4.2%</td>
<td>32 N</td>
</tr>
<tr>
<td>LC04</td>
<td>5.1%</td>
<td>52 N</td>
</tr>
<tr>
<td>Average</td>
<td>4.7%</td>
<td>37 N</td>
</tr>
</tbody>
</table>

Table 3. Prediction accuracy and prediction errors of strain gauge measurements

<table>
<thead>
<tr>
<th>Sensor</th>
<th>Reference period</th>
<th>Monitoring period</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$e_p$</td>
<td>$e_s$</td>
</tr>
<tr>
<td>SG04</td>
<td>3.8%</td>
<td>6.2 µε</td>
</tr>
<tr>
<td>SG05</td>
<td>4.4%</td>
<td>4.9 µε</td>
</tr>
<tr>
<td>SG12</td>
<td>3.8%</td>
<td>10.5 µε</td>
</tr>
<tr>
<td>SG13</td>
<td>2.2%</td>
<td>4.5 µε</td>
</tr>
<tr>
<td>SG26</td>
<td>3.0%</td>
<td>9.8 µε</td>
</tr>
<tr>
<td>SG27</td>
<td>2.1%</td>
<td>6.1 µε</td>
</tr>
<tr>
<td>SG38</td>
<td>8.7%</td>
<td>22.7 µε</td>
</tr>
<tr>
<td>SG39</td>
<td>3.5%</td>
<td>5.9 µε</td>
</tr>
<tr>
<td>Average</td>
<td>4.0%</td>
<td>8.8 µε</td>
</tr>
</tbody>
</table>

Figure 14. LC02 predicted and measured response over a three-day period.

Figure 15. SG13 predicted and measured response over a three-day period.

The load cell PE signals are plotted in Figure 16. The signals in the monitoring period are much noisier than in the reference period. Tables 2 and 3 give $e_{PE}$ and range values. Although the
response ranges of the load cells in the monitoring period are smaller than in the reference period, the $\epsilon_{PE}$ values are greater than $\epsilon_0$ values, indicating that the regression models fail to offer the same degree of prediction accuracy for the new measurements. The strain gauge PE signals (see Figure 17) for the monitoring period are also less accurate than for the reference period, although the average $\epsilon_{PE}$ value is smaller than the average load cells $\epsilon_{PE}$ value. The strain ranges at some sensor locations for the monitoring period are even greater than for the reference period. The PE SG38 signal is the most erroneous. PE values at the beginning of the monitoring period even exceed 100µε, suggesting that either the regression models fail to predict the SG38 measurements or the sensor might be faulty. Further studies are required to gain a better understanding of the nature of such high signal variations.

one-week period (see Figure 13) give a brief insight into the variability of the observed strains. In this study the regression models were trained with a dataset comprising of measurements over a two-week period. The results show that although the response is predicted with reasonable accuracy, the desired accuracy ($\epsilon_{PE} < 5\%$) was not reached for multiple sensors for the monitoring period. The SG38 signals had the least accurate predictions. A histogram counting the number of measurements within a range of $\epsilon_{PE}$ values of PE SG13 and PE SG38 is shown as Figure 18. The PE SG38 curve has a long dip at the beginning of the monitoring period, which is reflected as the large distribution of measurements within the negative x-axis region. It also is much wider than the PE SG13 curve, indicating that large number of measurements are extremely erroneous (i.e. $\epsilon_{PE}$ is between -20% and 30%).

![Figure 16. The load cell PE signals. Signals are shifted along the y-axis for clarification.](image)

Although the reference period covers a wide range of temperature variations the global temperature increases as the month progresses. The number of hours of daylight also increases during the dataset collection period, therefore the bridge and surrounding environment are exposed to longer periods of high temperature as the period progresses, than at the beginning of May. This phenomenon could be reducing the accuracy of the thermal response prediction. Figure 19 shows T03 temperature measurements over a 30-hour period at the beginning and end of the dataset collection period. The average temperature the end of the period is higher than at its beginning. Also, the duration of high temperatures is longer at the end of the month than at its beginning.

![Figure 17. The strain gauge PE signals. Signals are shifted along y-axis for clarification](image)

**Discussion**

The MX3D Bridge not only has a unique shape, and is produced using a new novel construction material and manufacturing technique, but it also has a complex thermal response. The four strain gauge measurements collected over a

![Figure 18. Curve histogram of $\epsilon_{PE}$ for the one-week monitoring period.](image)

![Figure 19. T03 measurements over two 30 hour periods. The cross marks indicate the lowest temperatures in a 24-hour period.](image)
5 CONCLUSIONS

Metal 3D printing is starting to be explored as a manufacturing technique in the construction sector, with numerous benefits over traditional forming techniques, such as geometric freedom, reduced material usage and improved onsite safety. The first metal 3D printed structure, the MX3D Bridge, has had a bespoke sensor designed and installed to measure the short- and long-term structural performance, along with the collection of human interaction data as part of a ‘living laboratory’. Initial load, strain and thermal data collected during a nine-month testing and commissioning period at the University of Twente is presented in this study.

Conclusions from the first attempt to characterize thermal response of the MX3D Bridge are as follows:

- Although datasets of measurements collected over two weeks may be sufficient, the reference period needs to include the entire variability of the measurements for higher prediction accuracies.
- The load and temperature plots are similar in nature between individual sensors in each sensor type family, while the strain gauges tend to have unique signatures (see Figure 13).
- Although printed structures are expected to behave in a broadly similar manner to conventional structures, the complex geometric form, and anisotropic and non-uniform material properties present a unique challenge characterising their thermal response.

The work presented in this study is ongoing work. Once the MX3D Bridge is in its final location and measurements comprising at least one year will be recorded, the bridge thermal response will become clearer than it is now, opening opportunities for multiple publications.

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