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Correlation of natural frequencies of bridges that are under similar environmental conditions.

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ABSTRACT: While Structural Health Monitoring (SHM) has potential to aid bridge managers, its adoption has been limited, with one of the challenges being determining a bridge's condition without a historical reference point for that structure. Researchers have started investigating Population-Based Structural Health Monitoring (PBSHM) to tackle this, facilitating the sharing of data from comparable structures. The key advantage of PBSHM is that it potentially enables us to use data from one structure to make inferences about the health of another structure in the same population.
Whilst, to date, populations that have been used for PBSHM have been defined using structural similarities alone, you might be missing out on information that could be useful for bridge managers, which raises the question: Could we define populations in a different way? This research investigates if it is potentially useful to define a population of bridges based on whether they experience the same environmental conditions. To answer this, long-term natural frequency data from two bridges close to each other are analysed to determine the level of correlation between them. This work shows that it may be potentially useful to define populations based on factors other than structural similarities, which allows greater opportunities for PBSHM.

KEY WORDS: Structural Health Monitoring (SHM); Population-Based Structural Health Monitoring (PBSHM); Bridge Monitoring; Natural Frequencies; Environmental Effects; Correlation Analysis; Temperature Influence; Vibration Data; Graph-Based Structural Similarity; Machine Learning in SHM.

1 INTRODUCTION

1.1 Challenges in current bridge inspection

Bridges are vital pieces of infrastructure, enabling the movement of goods and people [1]. Currently, bridges are monitored primarily through periodic visual inspections, which provide valuable insights. However, these visual inspections can be subjective, and some defects, such as internal cracks or corrosion, may not be visible during routine inspections.

In the worst-case scenario, undetected structural deficiencies can lead to catastrophic bridge failures, resulting in substantial financial costs and loss of life. For example, in 2018 the Morandi Bridge failed, killing 43 [2]. Additionally, the subjectivity of visual inspections makes it challenging to efficiently allocate limited resources. In 2024, the Carola Bridge in Dresden, Germany, collapsed due to hydrogen-induced stress corrosion cracking in the bridge's steel components [3]. The aftermath of the collapse can be seen in Figure 1. This type of corrosion began during the bridge's construction between 1967 and 1971 and progressed internally over decades, remaining undetectable through standard visual inspections. The eventual collapse of the Carola Bridge is a good example of highlighting a significant limitation of traditional monitoring methods.

Figure 1. Carola Bridge (Dresden, 1971).

1.2 Background on Structural Health Monitoring (SHM)

Over the past 30 years, there has been increasing interest in using quantitative data, such as acceleration or displacement, to assess bridge health, a practice known as Structural Health Monitoring (SHM) [4]. Its widespread adoption has been limited, however, with one of the challenges being determining whether a bridge is healthy or damaged without a historical reference point for that structure. This process is challenging because SHM systems often rely on baseline data to detect structural deterioration. If you do not take measurements from the 'healthy' state, it is difficult to determine the difference between normal changes (caused by things like weather or traffic) and real damage, which raises the risk of false alarms or missed defects [4].

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1.3 Overview of Population-Based Structural Health Monitoring (PBSHM) to date and current limitations

Researchers have begun exploring Population-Based Structural Health Monitoring (PBSHM) as a solution to address the challenges in traditional SHM, enabling the sharing of data across comparable structures. It allows data from one structure to be used to make inferences about the health of another structure within the same 'population' [5].

The foundations of PBSHM have been established through a series of published papers *Towards Population-Based Structural Health Monitoring* [6, 5, 7, 8, 9, and 10]. These papers examine methods for representing structures as graphs and developing similarity measures to compare them.

PBSHM extends traditional SHM by focusing on monitoring populations of structures rather than individual assets. Unlike conventional SHM, which relies on baseline data for a single structure, PBSHM enables the transfer of knowledge across a group of similar structures. By leveraging data from one structure, engineers can make inferences about the condition of others within the population, helping to mitigate the challenge of missing baseline data [5].

However, for PBSHM to be effective, the population must consist of sufficiently similar structures. If the differences are too significant, knowledge transfer may become inaccurate, leading to negative transfer; indeed, the application of insights from one structure can act to introduce error rather than improving understanding [7].

In practice, populations of bridges in PBSHM are typically formed by identifying structures that are structurally similar. For instance, Gosliga et al. [11] identified a pair of similar truss footbridges and a group of two beam-and-slab bridges. These bridges were represented as graphs, and using a graph matching algorithm, a high similarity metric was observed. Following field testing, the authors compared their dynamic responses and confirmed that the frequencies and mode shapes of bridges identified as similar through graph matching were indeed consistent [12].

If populations are defined solely based on structural information, potentially valuable factors that could aid in SHM might be overlooked. This raises the question: Could populations be defined differently? For example, a population could include bridges within the same geographical area, meaning they would be subject to the same environmental conditions. While populations in PBSHM have thus far been considered based on structural similarity, exploring alternative conceptualisations of populations may prove to be equally useful.

1.4 Contribution of this work

To explore whether bridges located in close proximity and therefore notionally experiencing the same environmental conditions could potentially form a population, long-term natural frequency data from two bridges 540 metres apart were analysed to determine the level of correlation between them. The results suggest that defining populations based on factors other than structural similarities could be potentially valuable, offering greater opportunities for PBSHM.

2 BRIDGE SITES USED AND TEMPERATURE CORRELATION BETWEEN SITES

2.1 Bridge selection and data collection

For this study, two bridges located 540 metres apart along the same river were selected. Bridge 1 is a 98-metre-long, 27-metre-wide bowstring girder bridge (Figure 2a), while Bridge 2 is a 76-metre-long, three-span composite concrete and steel bridge (Figure 2b). The proximity of these bridges allowed for a controlled investigation of how environmental factors influenced their dynamic behaviour.

(a)

(b)

Figure 2. (a) Schematic of Bridge 1 (b) Schematic of Bridge 2.

As described by O'Higgins et al. [13], long-term vibration data was collected using a single accelerometer on each bridge. It was observed that positioning the sensor near the quarter-span point on both bridges allowed it to detect most modes and frequencies.

The Structural Health Monitoring (SHM) system used for long-term monitoring consisted of one MEMS accelerometer and one environmental sensor. The accelerometer employed was the Multifunction Extended Life (MEL) Data Logger from Gulf Coast Data Concepts. This accelerometer was housed in an enclosure, which was then attached to the deck of each bridge. One of these enclosures is shown in Figure 3.

The environmental variables were measured using an environmental sensor capable of recording both air temperature and humidity. To ensure accurate temperature readings, the sensors were not placed within the enclosure to avoid the effects of solar gain. Instead, they were positioned out of direct sunlight to provide a representative measure of the local air temperature. On each bridge, the temperature sensors were placed on the abutment shelf or at the base of an abutment, both out of direct sunlight.

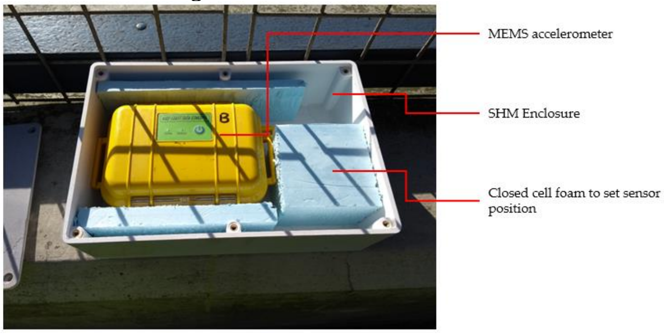

Figure 3. Monitoring enclosure and MEL data.

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2.2 *Correlation of temperature data*

A key objective of this study was to determine whether the two bridges experienced similar environmental conditions. To assess this, temperature data from both bridges were compared using a hexbin plot (Figure 4). A hexbin plot is a 2D histogram where the bins are hexagonal, and the colour intensity represents the number of data points within each bin.

Figure 4 shows a strong positive correlation between the temperature measurements of both bridges, with a correlation coefficient of 0.98, indicating that higher temperatures on Bridge 2 correspond to higher temperatures on Bridge 1. This suggests that the two bridges experience nearly identical environmental exposure.

However, some variability was observed between January 6 and February 17, during which Bridge 1 exhibited slightly higher temperatures in the 0-5°C and 5-10°C ranges. The cause of these anomalies remains uncertain, but potential explanations include differential shading and differences in material thermal properties.

While these discrepancies are noticeable in the plot, they do not significantly impact the overall trend. There are up to 14,000 data points in the yellow bins and fewer than 2,000 data points in the dark blue bins, reinforcing the stability of the best-fit line. This indicates that most of the data follows a linear relationship, with only a brief period showing anomalous values.

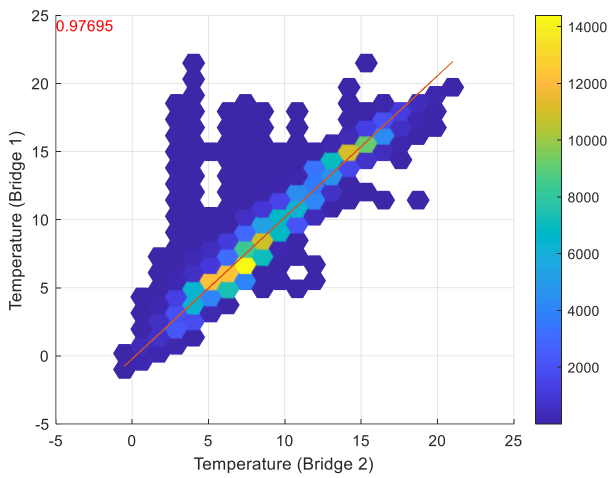

Figure 4. Temperature data from Bridge 1 versus temperature data from Bridge 2.

3 NATURAL FREQUENCY ANALYSIS

3.1 *Extraction of Natural Frequency*

As per O'Higgins et al. [13], acceleration data was segmented into 30-minute intervals and processed using the Stochastic Subspace Identification (SSI) method to extract the bridge frequencies. The data was recorded from October 2018 to May 2021, though some gaps occurred due to limited personnel availability for data collection and disruptions caused by the COVID-19 pandemic.

For this work, a simple outlier analysis was undertaken on natural frequency data so that the complexity of data analysis was reduced and data visualisation was clearer. Any data point that was more than three scaled median absolute deviations from the median of the data was removed.

3.2 *Time-domain work*

Figure 5 presents the time-series data for the natural frequencies of both bridges. Bridge 1 exhibits five natural frequencies ranging from approximately 1.2 Hz to 5.2 Hz, while Bridge 2 has five natural frequencies ranging from approximately 2.7 Hz to 9.3 Hz. Overall, Bridge 2 demonstrates higher frequency values compared to Bridge 1.

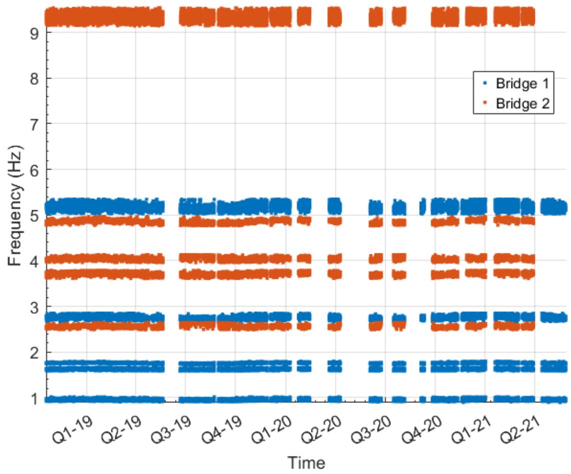

Figure 5. All frequency data over the whole monitoring period.

Figure 6 consists of two subplots, both illustrating the relationship between bridge frequencies and temperature over time. Frequency and temperature are plotted against the left and right vertical axes, respectively.

In plot (a), the temperature (purple line) exhibits seasonal variations, with distinct peaks and troughs. When analysing annual data, a seasonal trend is observed for frequency 5 of Bridge 1 and frequency 4 of Bridge 2, with evidence of an inverse correlation between the frequencies and temperature. Additionally, Bridge 1 and Bridge 2 appear correlated, with both bridges showing an inverse relationship with temperature on an annual scale.

In plot (b), which focuses on daily temperature cycles, there is some correlation between the two frequencies. As seen in plot (a), higher temperatures correspond to lower frequency values, a trend that is even more noticeable in plot (b). This aligns with expectations, as increasing temperature may cause a reduction in structural stiffness, leading to lower natural frequencies [14].

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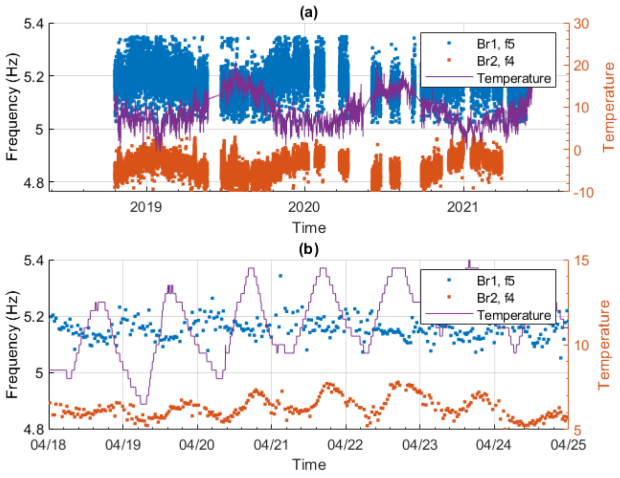

Figure 6. Frequency 5 of Bridge 1 and frequency 4 of Bridge 2 (a) Whole monitoring period (b) A week of monitoring data.

3.3 Frequency correlation work

Figure 7 presents hexbin plots for all the frequencies of Bridges 1 and 2, with the correlation coefficient displayed in the top left corner of each plot. The histograms on the diagonal illustrate the distribution of each frequency.

The figure reveals a strong correlation between frequencies within the same bridge (rows 1-5, columns 1-5). However, the most relevant information is in the top right section of the figure, highlighted by a dashed black box, which shows the correlation between frequencies of Bridge 1 and Bridge 2. The column references (1 to 10) are displayed at the top, while the row references are shown on the right.

For example, the plot in row 1, column 6 represents the correlation between frequency 1 of Bridge 1 and frequency 1 of Bridge 2, with a correlation coefficient of 0.31, indicating a relatively weak correlation. Similarly, the plot in row 1, column 7 shows the correlation between frequency 1 of Bridge 1 and frequency 2 of Bridge 2, with a coefficient of 0.5. A zoomed-in view of the area inside the dashed black box in Figure 7 is shown in Figure 8. Figure 8 illustrates the varying correlations between frequencies, with correlation coefficients ranging from 0.13 to 0.64.

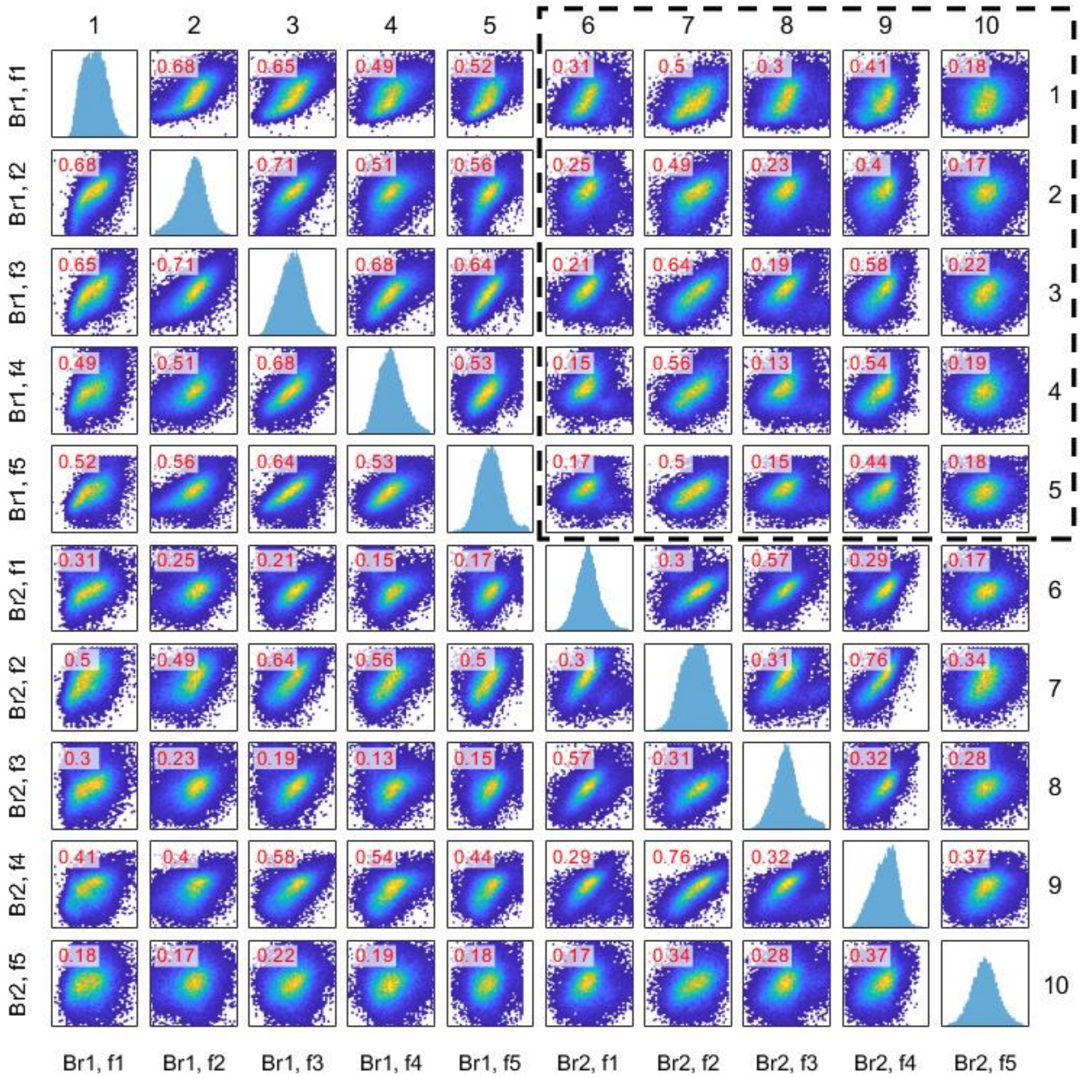

Figure 7. All correlation plots for all the frequencies.

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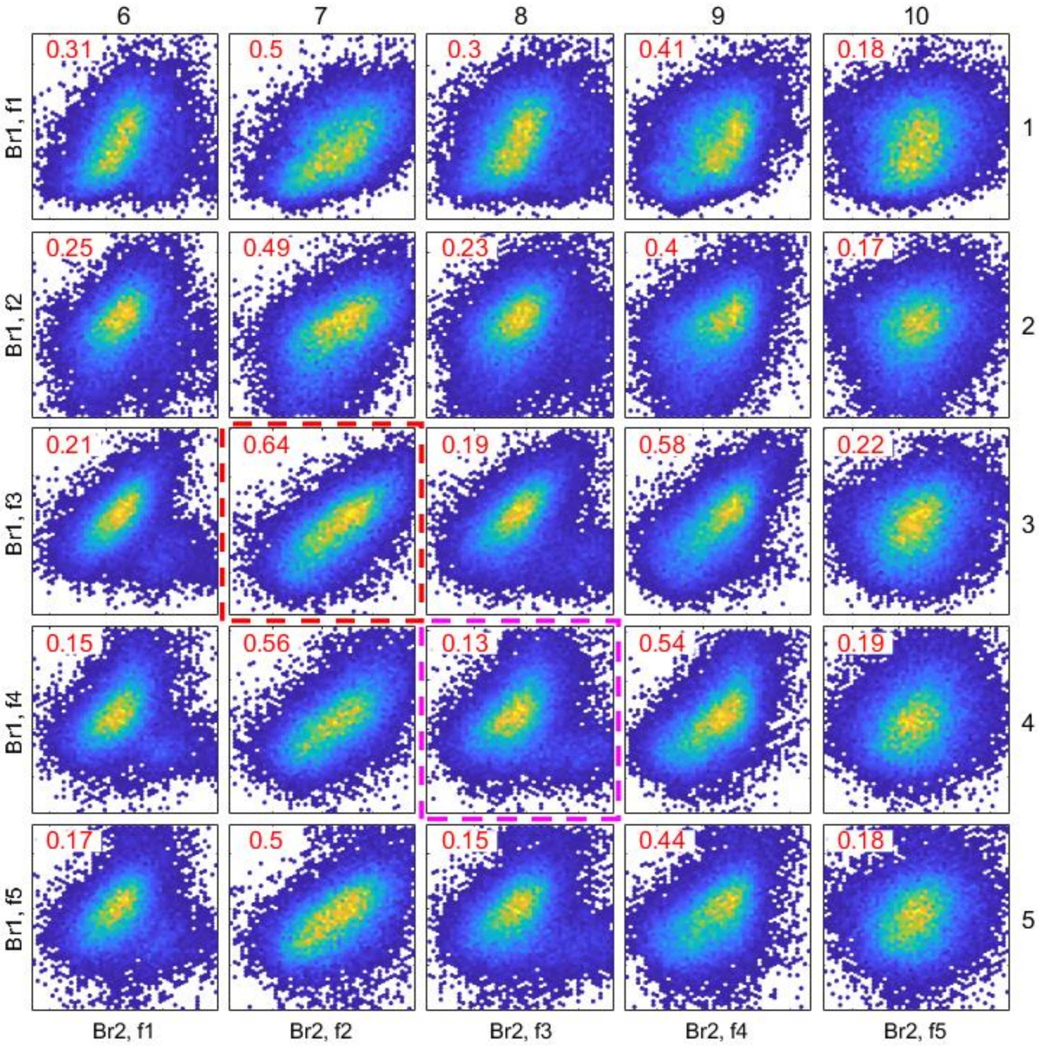

Figure 8. Correlation between pairs of frequencies in Bridge 1 and Bridge 2.

The highest correlation of 0.64 is observed between frequency 3 of Bridge 1 and frequency 2 of Bridge 2 (shown in row 3, column 7 in the dashed red box in Figure 8), and this is shown on a larger scale in Figure 9.

The lowest correlation of 0.13 is observed between frequency 4 of Bridge 1 and frequency 3 of Bridge 2 (shown in row 4, column 8 in the dashed magenta box in Figure 8), and this is shown on a larger scale in Figure 10.

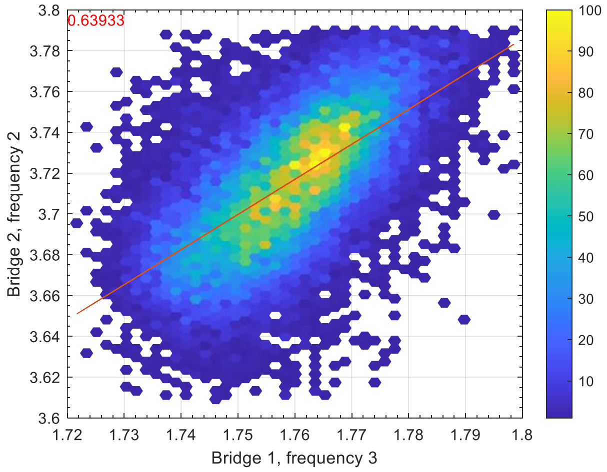

Figure 9. Most correlation between frequencies.

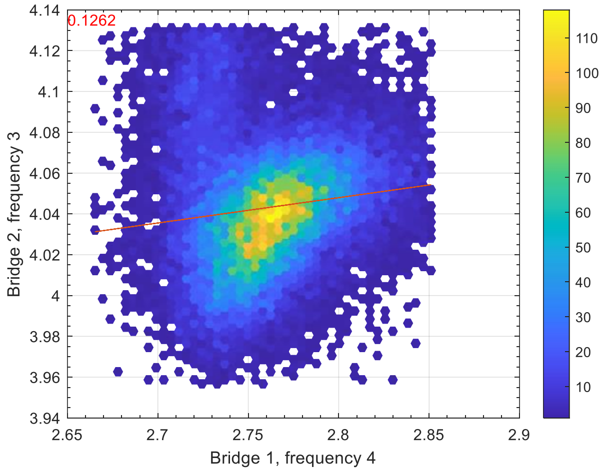

Figure 10. Least correlation between frequencies.

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Having identified the pair of frequencies with the highest correlation (Figure 9) and the lowest correlation (Figure 10), we now look at the time series plots associated with these frequencies to try and get further insight into why some are better correlated than others. To this end, Figure 11 presents the pair of frequencies with the highest correlation, specifically frequency 3 of Bridge 1 (plotted against the left-hand vertical axis) and frequency 2 of Bridge 2 (plotted against the right-hand vertical axis). Plot (a) displays data spanning the entire monitoring period from October 2018 to May 2021, while plot (b) focuses on a 7-day period. The strong correlation between these frequencies is evident from the synchronised sinusoidal patterns observed in both bridges.

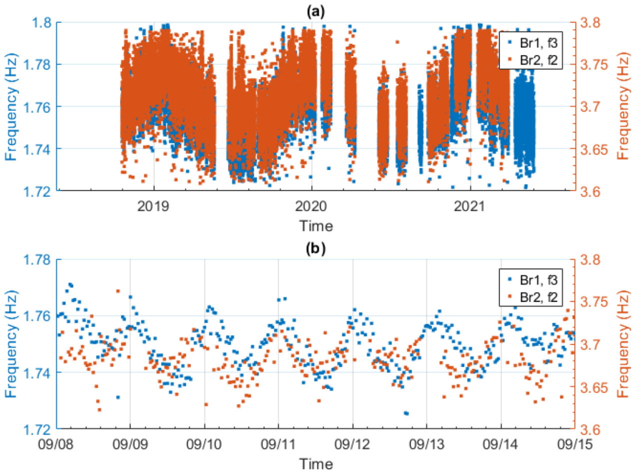

Figure 11. Frequency 3 of Bridge 1 and frequency 2 of Bridge 2 (a) Whole monitoring period (b) A week of monitoring data.

Figure 12 shows the least correlated frequencies between both bridges, specifically frequency 4 of Bridge 1 and frequency 3 of Bridge 2. This figure follows the same format as Figure 11, with the overall monitoring period shown in plot (a) and the same 7-day period shown in plot (b). When plotted as a time series, these natural frequencies exhibit a lower correlation to those shown in Figure 11, which is consistent with the expectations based on the hexbin plot in Figure 10.

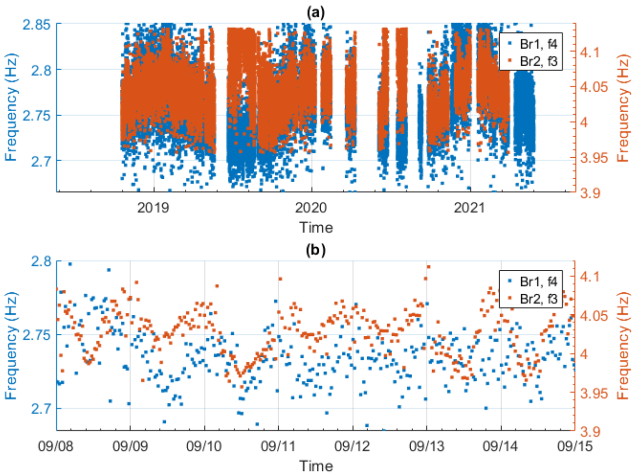

Figure 11. Frequency 4 of Bridge 1 and frequency 3 of Bridge 2 (a) Whole monitoring period (b) A week of monitoring data.

4 CONCLUSION

Temperature data from two bridges located near each other shows a strong correlation (with a correlation coefficient of 0.98), suggesting that the bridges experience similar environmental conditions. The natural frequencies of the two bridges also exhibit significant correlation, with coefficient values for some pairs of frequencies reaching up to 0.64. Traditionally, Population-Based Structural Health Monitoring (PBSHM) has defined populations based on structural similarities. This paper suggests the potential for defining populations based on shared environmental conditions. Given the sufficient correlation in temperature and frequency data, it may be possible to infer information about Bridge 1 based on the data collected from Bridge 2. This will be further explored in future work through correlation analysis, such as cointegration on the data.

Future studies will examine a wider range of bridge types to determine whether the same correlations apply. Additional research could also explore the conditions under which these correlations remain valid and when they begin to break down.

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