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TRANSFER LEARNING FOR SHM USING A REPRESENTATIVE BRIDGE

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Abstract. *Continuous monitoring of civil engineering structures has become increasingly important due to the growing impact of environmental actions and aging effects on structural performance. In this context, sensor-based Structural Health Monitoring (SHM) systems provide essential real-time information to support preventive maintenance and informed decision-making.*

This study focuses on the development of predictive models capable of estimating certain structural parameters using limited information from similar structures. In fact, the monitored structure is a prestressed concrete overpass representative of many similar infrastructures built in Portugal during the same period, making it suitable as a reference structure for Transfer Learning applications.

The experimental campaign included ambient vibration tests for modal identification, complemented by continuous monitoring using customized temperature and displacement sensors installed at critical sections. The collected data were decomposed into daily and annual trend components. The phase delay effects between temperature and displacement were identified and corrected, and regression models were developed to describe the relationship between thermal actions and structural response.

The results demonstrate a strong correlation between temperature variations and structural displacements, enabling accurate estimation of displacement components using temperature data. The proposed methodology supports the idea of transfer of behavioral relationships between similar structures and contributes to the development of scalable and cost-effective monitoring strategies for large networks of roadway infrastructures.

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1 STRUCTURAL HEALTH MONITORING

Structural Health Monitoring (SHM) constitutes a fundamental tool for the continuous assessment of structural performance throughout the service life of infrastructures [1-6]. The development and implementation of SHM systems have gained increasing relevance in recent decades, particularly due to the widespread ageing of infrastructures, the increase in traffic and safety demands, and the need to optimize maintenance strategies [3,7-8].

SHM systems are based on the installation of sensors at strategic locations within the structure, enabling the continuous or periodic acquisition of data related to its structural response. Among the most commonly monitored parameters are accelerations, displacements, strains, and temperature, which allow the characterization of structural behavior under different loading and environmental conditions. The analysis of these data enables the identification of changes in structural behavior over time, contributing to the early detection of anomalies and to the evaluation of the evolution of potential degradation mechanisms [4,5,9].

Despite technological advances, commercial monitoring systems often involve high costs and may be difficult to implement in certain structures. Many infrastructures are located in areas with limited accessibility or without continuous electrical power supply, requiring significant adaptations that are not always compatible with existing commercial equipment. These limitations have motivated the development and use of customized sensors, which offer several advantages, including reduced manufacturing costs, the possibility of integration with wireless communication systems, compact dimensions that facilitate their incorporation into the structure, low maintenance requirements, and flexibility in the selection of power sources, including batteries or solar panels [4-5].

In the context of bridges, the application of SHM systems is of particular importance due to the critical role of these infrastructures in transportation networks and the significant impact that structural failures may have on safety and mobility [10]. Additionally, the structural response of bridges is strongly influenced by environmental conditions, among which temperature plays a major role, inducing significant variations in structural parameters such as displacements, strains, and natural frequencies. These thermal variations may mask structural changes associated with damage, making the correct interpretation of environmental effects essential in the analysis of monitoring data [11].

Despite the advantages associated with SHM systems, their widespread implementation across large infrastructure networks remains limited by economic and operational constraints [4]. Therefore, it becomes necessary to develop methodologies that maximize the use of information collected from instrumented structures, contributing to a more efficient assessment of structural behavior at a large scale and establishing the foundation for the adoption of knowledge-reuse approaches [12].

2 TRANSFER LEARNING

Due to economic, operational, and accessibility limitations that hinder the individual instrumentation of a large number of infrastructures, the development of more efficient and scalable monitoring methodologies become necessary [13-14]. In this context, Transfer Learning (TL) emerges as a promising approach, representing a subfield of Machine Learning (ML) based on the reuse of previously acquired knowledge to improve the interpretation or prediction of a new related problem. In contrast to the traditional ML paradigm, which assumes that training and testing data belong to the same statistical distribution, TL allows different domains and tasks to be related, enabling the transfer of relevant information between distinct scenarios [45-16].

Within the context of Structural Health Monitoring (SHM), Transfer Learning assumes particular relevance in infrastructure networks composed of multiple structures with similar typologies, such as road bridges and overpasses [17]. The use of data obtained from previously monitored structures, calibrated numerical models, or previously identified behavioral patterns makes it possible to reduce the need for extensive experimental campaigns for each new structure, thereby contributing to the optimization of available resources [11].

In the field of bridge engineering, this approach has led to the development of the concept of Population-Based Structural Health Monitoring (PBSHM), in which multiple structurally similar infrastructures are analyzed in an integrated manner [12,17]. Within this framework, the information collected from a reduced number of representative structures can be used to support the assessment of other infrastructures with comparable geometric and structural characteristics, contributing to the reduction of long-term monitoring costs [14].

The literature on Transfer Learning in SHM indicates that different types of variables may be used as structural features. Among these, natural frequencies are the most commonly used due to their sensitivity to changes in structural stiffness and their relative ease of estimation from dynamic testing [17-19]. However, other variables, such as displacements and temperature, have gained increasing importance, particularly in studies focused on structural response under environmental actions [13,17].

Displacements represent a direct measure of structural response and can be used to characterize the global structural behavior over time. Although less frequently explored in classical TL applications based on vibration data, recent studies demonstrate their potential when combined with numerical models or domain adaptation techniques [13-14]. On the other hand, temperature constitutes a dominant environmental variable in bridge behavior, being responsible for significant structural variations at the level of displacements and other structural parameters. Therefore, the explicit consideration of thermal effects is essential to ensure model robustness and to avoid misinterpretations associated with environmental variations [13-14,17].

3 DESCRIPTION AND IDENTIFIED PATHOLOGIES OF THE STRUCTURE UNDER STUDY

The structure analyzed in this study is a reinforced and prestressed concrete road overpass constructed in 1979. It was designed to provide connectivity between two roadway branches located at different elevations and is representative of a structural typology widely used in the Portuguese road network during the 1970s and 1980s.

After more than four decades of service, several structural pathologies were identified, leading to the implementation of rehabilitation measures and the installation of a Structural Health Monitoring (SHM) system. The selection of this structure as a case study was also motivated by its representativeness within a broader population of similar overpasses, making it suitable as a reference structure for Transfer Learning applications.

3.1 Description of the structure

The overpass under study consists of a continuous prestressed reinforced concrete deck with three spans, including a central span of 25.87 m and two side spans of 8.62 m, resulting in a total structural length of approximately 43.12 m, as illustrated in Figure 1.

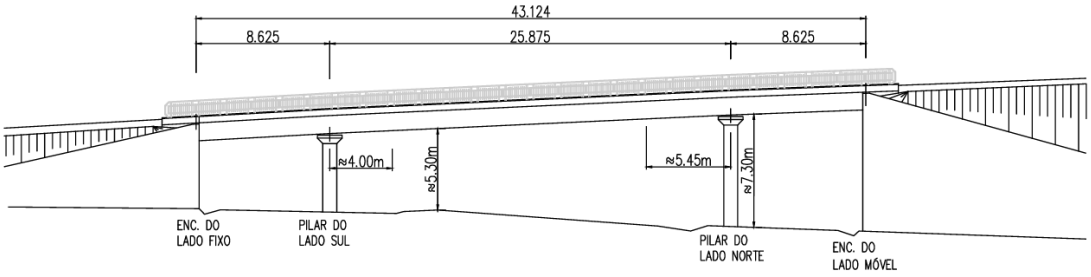


Figure 1. Longitudinal geometric configuration of the structure.

The deck has a total width of 9.29 m and is supported by two circular reinforced concrete columns with a diameter of 0.90 m, as shown in Figure 2. Elastomeric bearings are installed between the deck and the columns, allowing structural displacements, particularly those associated with thermal variations.

Regarding the abutments, the southern abutment was designed as a fixed support in both longitudinal and transverse directions, while the northern abutment allows longitudinal displacements while remaining fixed in the transverse direction. This structural configuration enables the accommodation of longitudinal deck movements induced by temperature variations and service loads.

Additionally, the structure includes wing walls connected to the abutments, designed to retain adjacent embankments and ensure the stability of the surrounding soil mass [20].

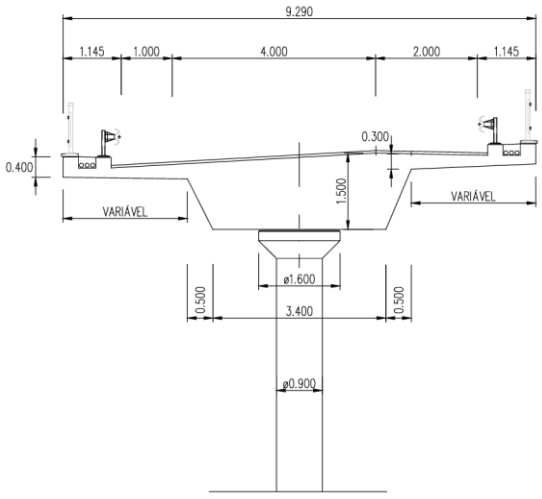


Figure 2. Transverse geometric configuration of the structure.

3.2 Identified Pathologies

According to the inspection report, the structural assessment included both visual inspections and complementary testing procedures. These included measurements of concrete cover thickness, carbonation depth evaluation, electrical resistivity testing, and non-destructive testing using ground-penetrating radar (GPR) and ultrasonic techniques.

The results of these inspections allowed the identification of the main structural pathologies affecting the structure. Two transverse cracks were detected in the deck, located in the central span at approximately 4 m from each column, with an estimated depth of approximately 20 cm.

Delamination of the surface layers was also observed in the abutment and wing walls, accompanied by outward rotation of these elements. Maximum displacements of approximately 12 cm were recorded at the upper extremities of the wing walls.

Additionally, localized corrosion of metallic elements embedded near the concrete surface was identified, resulting in small areas of concrete spalling and localized surface deterioration [21].

4 MONITORING SYSTEM

The monitoring system implemented in this study includes customized temperature and displacement sensors specifically developed to meet the requirements of bridge instrumentation under limited accessibility conditions. The sensors were developed at the Faculty of Engineering of the University of Porto (FEUP), aiming to provide reliable measurements while maintaining low implementation costs.

The instrumentation strategy was designed to capture the thermal behavior of the structure and its influence on structural displacements at critical locations. Temperature sensors were installed in representative sections of the main beam, while displacement sensors were positioned to measure relative movements between structural elements.

4.1 Temperature Sensors

The temperature sensors employed in the instrumentation system are digital sensors encapsulated in metallic cylinders with dimensions of 5 × 30 mm, model DS18B20, manufactured by Maxim Integrated (Figure 3). These sensors are capable of measuring temperatures within a range of −55°C to +125°C, with an accuracy of ±0.5°C within the temperature interval between −10°C and +85°C.

Two temperature sensors were installed in the structure, with data recorded every 10 minutes. One sensor was positioned at the lower side of the flange, while the second sensor was installed within the solid region of the beam, as shown in the **Figure 3**. This configuration was selected to capture representative temperature variations within the structural element and to evaluate their influence on the measured structural displacements.

The placement of temperature sensors within the beam was defined considering the expected thermal response of the structure and the need to obtain representative temperature data associated with structural movement.



Figure 3. Temperature Sensors.

4.2 Displacements Sensors

The displacement sensor used in this monitoring system consists of customized cylindrical devices approximately 25 cm in length and 6 cm in diameter, installed inside rectangular protective enclosures that integrate power supply and data acquisition components.

Each sensor includes a telescopic rod fixed between two distinct structural points, such as expansion joints or cracks, allowing the measurement of relative displacements between structural elements. The sensors have a maximum measurement range of 150 mm with a resolution of 0.01 mm. The effective measurement length can be adjusted according to the expected displacement range in each application.

During the initial phase of the experimental campaign, two displacement sensors were installed to evaluate the structural response and identify suitable locations for long-term monitoring. According to the original design expectations, the primary measurement location was defined between the deck and the northern abutment. However, no significant relative movements were detected at this location.

Conversely, measurable relative displacements were identified between the abutments and the wing walls. Based on these observations, the final installation was defined between the southern abutment and the corresponding wing wall A, where consistent structural movement was recorded (**Figure 4**).



Figure 4. Displacement Sensor.

5 DATA PROCESSING

The monitoring data was processed to identify the main thermal and mechanical components governing the structural response. Since the objective of this study is to establish predictive relationships between temperature and displacement, the raw signals were treated to isolate components associated with different time scales and to improve the interpretation of their correlation.

The adopted data processing methodology included three main steps: (i) decomposition of temperature and displacement signals into annual trend and daily components, (ii) identification and correction of the phase delay between thermal and displacement responses, and (iii) development of regression relationships between the processed variables. This procedure allowed the separation of short-term and seasonal trend effects, enabling a more consistent description of the influence of temperature on structural displacements.

Due to the limited duration of the available monitoring records, long-term trend effects were not considered in the present study. Therefore, the analysis was focused on the daily and annual trend components of both temperature and displacement.

5.1 Signal Decomposition

Temperature variations in structural elements may be decomposed into different components associated with distinct time scales, namely annual trend and daily components. The daily component is mainly related to the day–night cycle and solar radiation effects, while the annual trend component reflects seasonal temperature variations. Under the assumptions adopted in this study, the measured temperature signal may be expressed as:

$$T(t) = T_{annual\,trend}(t) + T_{daily}(t) \tag{1}$$

The decomposition of the temperature signal was carried out using digital filtering techniques in the frequency domain, allowing the separation of the annual trend and daily components. To define the filtering parameters, the normalized cut-off frequency, f_{nco}, was determined with respect to the Nyquist frequency according to:

$$f_{nco} = \frac{n}{f_s/2} \tag{2}$$

where n corresponds to the number of cycles associated with the phenomenon under analysis and f_s is the sampling frequency.

Temperature data were acquired at 10-minute intervals, corresponding to 144 samples per day. Considering one cycle per day, the normalized frequency associated with the daily component is given by:

$$f_{nco} = \frac{1}{72} = 0.013889 \tag{3}$$

The annual trend temperature component was obtained by removing the frequencies associated with the daily variation and higher-frequency fluctuations, preserving only the low-frequency content of the signal. This process was carried out by applying a fourth-order Butterworth low-pass filter, defined by a normalized cut-off frequency set to 0.009. The selection of this cut-off frequency incorporated a safety margin to ensure the effective removal of the daily component from the filtered signal. The value was further refined through an iterative adjustment process to obtain a smoother and physically representative annual trend temperature curve.

Similarly, the daily temperature component was obtained by applying a filtering procedure aimed at removing the low-frequency content associated with the annual trend component. Although a high-pass filter could be used for this purpose, when temperature signals contain higher-frequency components, as typically observed in field measurements, the use of a band-pass filter centered on the daily variation (1 cycle/day) provides a more suitable solution.

Accordingly, the lower normalized cut-off frequency was defined as 0.01, while the upper normalized cut-off frequency was set to 0.05. The upper limit was determined through an iterative evaluation process to avoid excessive high-frequency noise while preserving the dominant daily thermal oscillation. A fourth-order Butterworth band-pass filter was adopted due to its stable and monotonic frequency response, minimizing signal distortion during the filtering process.

The same filtering approach was applied to the displacement time series to ensure consistency between temperature and displacement component separation. Therefore, the total displacement signal was also decomposed into annual trend and daily components according to:

$$D(t) = D_{annual\ trend}(t) + D_{daily}(t) \quad (4)$$

where $D(t)$ represents the total displacement, while $D_{annual}(t)$ and $D_{daily}(t)$ correspond to the annual trend and daily displacement components, respectively.

5.2 Phase Delay Analysis

After signal decomposition, a time delay between temperature variations and displacement response was identified. This delay is associated with the fact that the structural response is not instantaneous, since heat propagation through structural elements requires time before producing measurable thermal deformations.

To account for this effect, a phase correction procedure was applied to align temperature and displacement signals. The delay was evaluated by identifying the time at which displacement peaks occurred and comparing these instants with the corresponding thermal response of the beam, considered as the reference temperature measurement.

For each daily cycle, the time corresponding to the displacement peak was identified and compared with the time of the corresponding temperature peak. The time differences obtained for each cycle were then statistically analyzed by calculating the mean, median and mode values. These statistical indicators were used to define a representative phase correction value.

Different phase correction values were identified for summer and winter periods. During winter conditions, smaller phase delays were observed due to reduced thermal amplitudes and lower temperature gradients. In the present study, a phase correction of 0 h 30 min was adopted for the winter period, resulting in improved alignment between the daily temperature and displacement components and enhancing the reliability of subsequent correlation analyses (**Figure 5**).

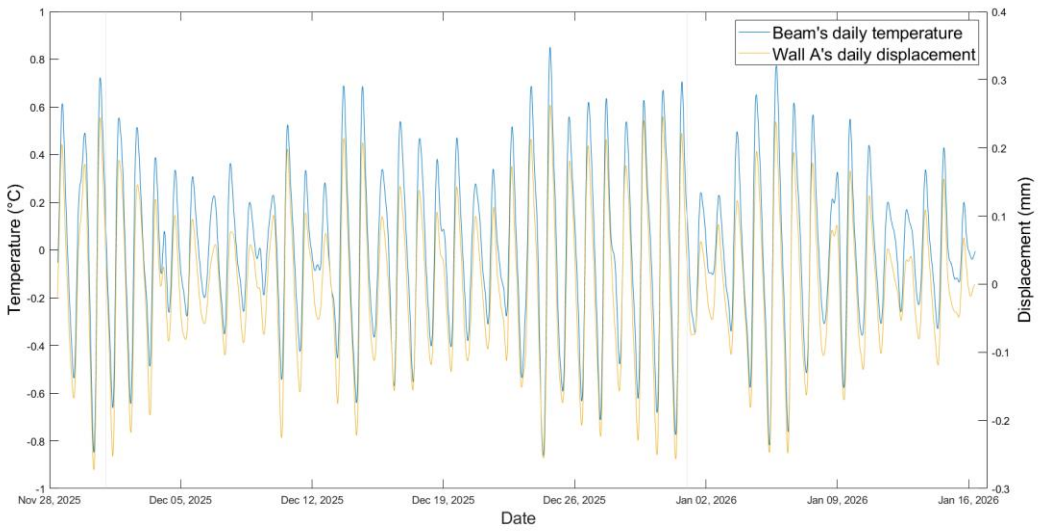


Figure 5. Daily temperature and displacement components after phase adjustment.

6 RESULTS AND DISCUSSION

After signal processing and phase alignment, the relationship between temperature variations and structural displacement was analyzed in order to evaluate the influence of thermal actions on the structural response. The decomposition of signals into daily and annual trend

components allowed a more detailed interpretation of short-term and seasonal structural behavior.

The results obtained from the monitoring data demonstrate a strong dependency between temperature variations measured in the beam and the displacement response recorded at the monitored location. The following subsections present the correlation analysis and the development of predictive models based on the processed signals.

6.1 Correlation between temperature and displacement

After phase alignment, a strong correlation was observed between the temperature measured in the beam and the displacement recorded at the monitored location (wall A), for both winter and summer periods. Considering the daily temperature component of the beam as the reference variable, a correlation coefficient of 0.9737 was obtained for winter period, indicating a very strong linear relationship between temperature variations and structural displacement (**Figure 6**).

Considering the annual trend component of the beam temperature as the reference variable, a correlation coefficient of 0.8972 was obtained for the winter period (Figure 7), which, although lower than the value obtained for the daily component, still indicates an adequate linear relationship between the analyzed variables.

The correlation and corresponding linear relationship were obtained using linear least-squares regression applied to the processed temperature and displacement data. The regression analysis was performed using Microsoft Excel, enabling the identification of predictive relationships between thermal variations and structural displacement response.

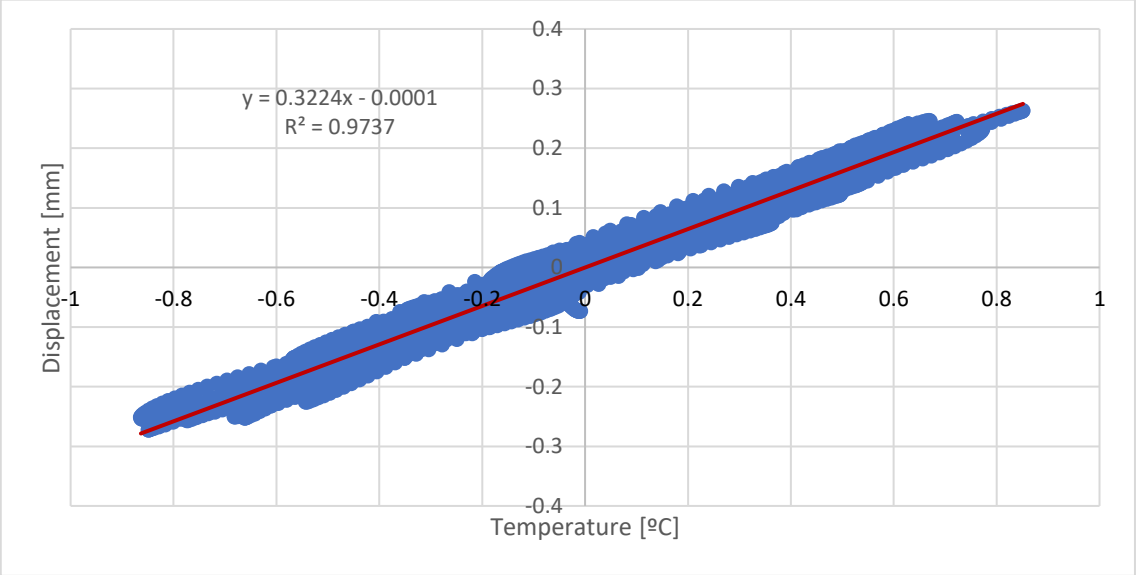


Figure 6. Correlation between daily temperature component and displacement.

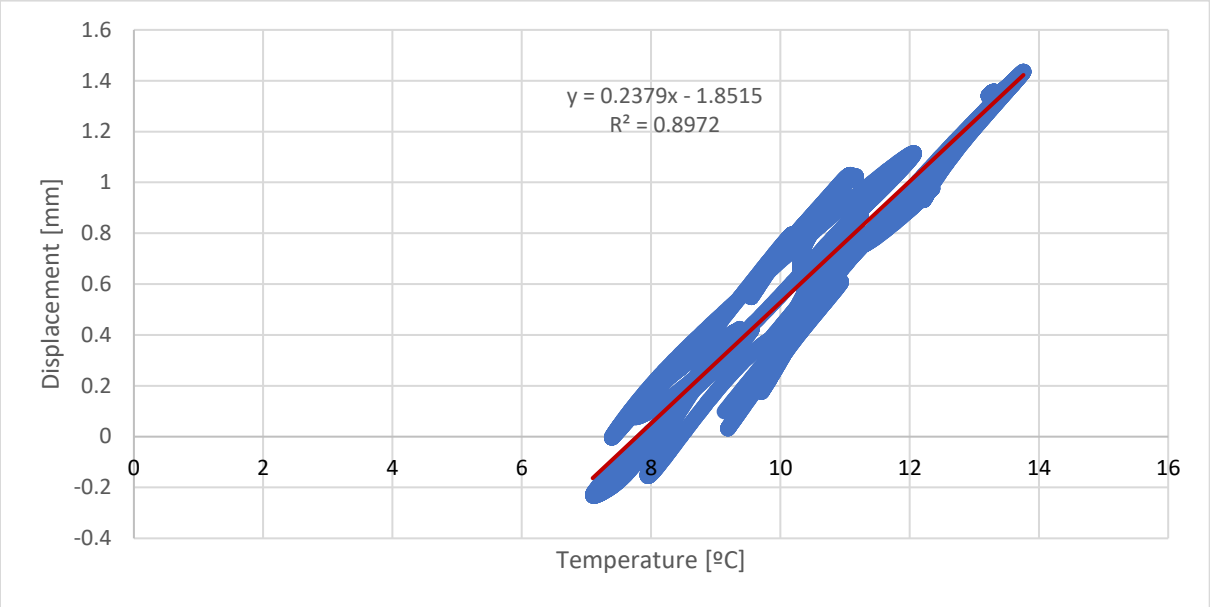


Figure 7. Correlation between annual trend temperature component and displacement.

This behavior confirms that thermal effects constitute the dominant mechanism governing the cyclic displacement response of the structure. In general, temperature increases lead to displacement increments due to thermal expansion of structural elements, while temperature decreases produce movements in the opposite direction.

The strong correlation obtained demonstrates that the daily thermal component plays a fundamental role in short-term displacement behavior, whereas the annual thermal trend component contributes significantly to medium- and long-term displacement behavior, reflecting the influence of seasonal temperature variations on the overall structural response. These findings support the development of predictive relationships based on temperature measurements.

6.2 Displacement Prediction Models

Based on the observed correlation between temperature and displacement components, predictive regression equations were established to estimate structural displacement from temperature measurements. These relationships represent a key step toward enabling displacement estimation using reduced monitoring data.

The regression equations were derived using linear least-squares regression applied to the decomposed temperature and displacement components. The resulting regression models were estimated separately for winter and summer periods, reflecting the different thermal behaviors observed in each season. For clarity, the results obtained for the winter period are presented herein as a representative example.

For the winter period, the daily displacement component can be estimated using the following regression equation:

$$D_{W,Daily}^{Est} = 0.3224 * T_{W,Daily} - 0{,}0001 \quad (5)$$

where:

$D_{W,Daily}^{Est}$: estimated daily displacement component in winter.

$T_{W,Daily}$: measured daily temperature component in winter.

Figure 8 presents the comparison between measured and estimated daily displacement components for the winter period. A very good agreement between both signals can be observed,

demonstrating the capability of the regression model to accurately reproduce the daily structural response.

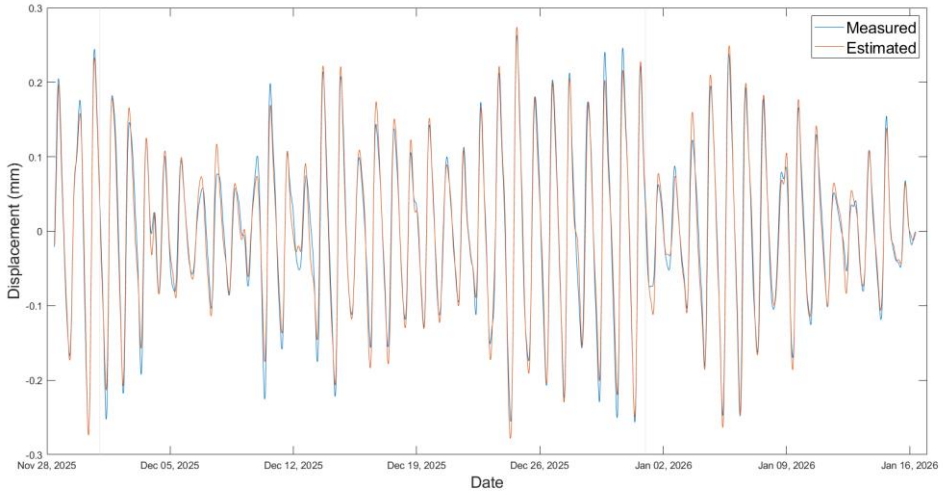


Figure 8. Measured and estimated daily displacement component (winter period).

For the annual trend component during winter conditions, a similar regression procedure was applied, based on the observed similarity between the annual trend temperature component and the corresponding annual trend displacement response. This similarity reflects the long-term thermal behavior of the structure and its influence on global structural movements. The resulting regression relationship is expressed as follows:

$$D_{W,Annual}^{Est} = 0.2379 * T_{W,Annual} - 1{,}8515 \quad (6)$$

where:

$D_{W,Annual}^{Est}$: estimated annual trend displacement component in winter.

$T_{W,Annual}$: measured annual trend temperature component in winter.

The comparison between measured and estimated annual trend displacement components is presented in Figure 9, showing consistent agreement between both signals.

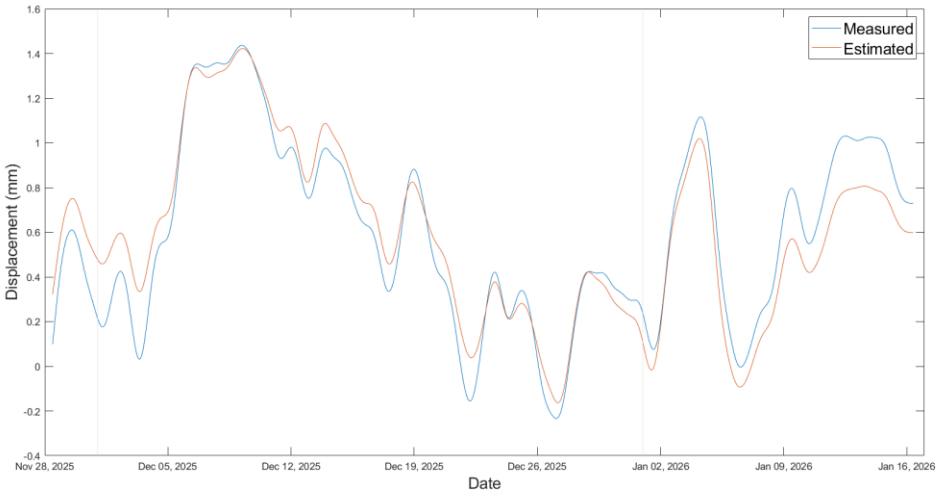


Figure 9. Measured and estimated annual trend displacement component (winter period).

By combining the daily and annual trend displacement components, it is possible to estimate the total structural displacement. For the winter period, the total displacement was obtained by summing the contributions from Equations (5) and (6), resulting in a reconstructed displacement signal representative of the overall structural response.

The comparison between measured and estimated total displacement is presented in Figure 10, where a strong agreement between both signals can be observed. Although small differences can be identified in the absolute displacement values, the relative variations between measured and estimated signals show a very consistent behavior over time.

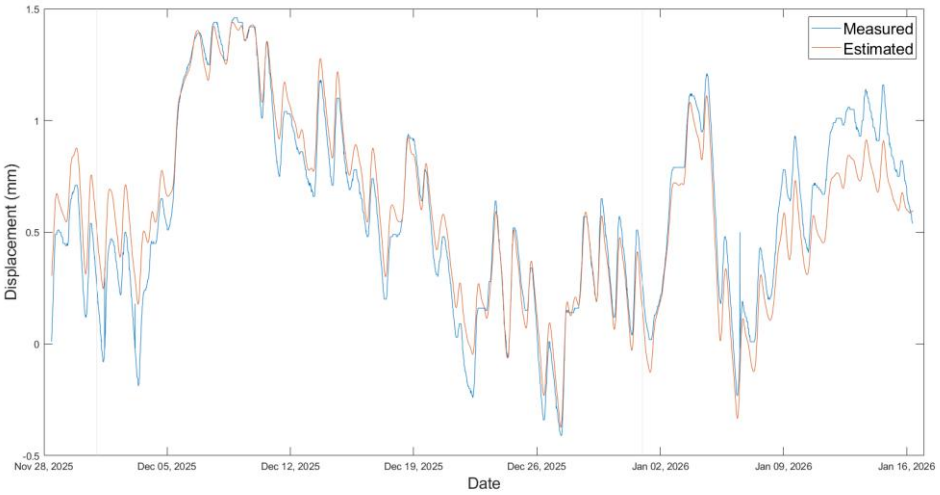


Figure 10. Measured and estimated total displacement (winter period).

This result demonstrates that the combined use of daily and annual trend temperature components provides an effective representation of the overall structural displacement behavior. The ability of the proposed model to accurately reproduce the relative displacement trends confirms its suitability for predicting structural behavior based on temperature measurements.

Furthermore, the good agreement obtained between measured and estimated displacement variations supports the applicability of the proposed predictive equations for estimating structural response in similar structures using limited monitoring data.

7 CONCLUSION

The obtained regression equations provide a promising tool for estimating displacement behavior using temperature measurements, supporting the development of transferable behavioral models for similar structures.

The regression equations obtained in this study constitute a practical and reliable tool for estimating displacement behavior based on temperature measurements, contributing to the development of transferable behavioral models applicable to structurally similar infrastructures. The main contributions of this work can be summarized as follows:

• Development and implementation of customized low-cost displacement sensors suitable for long-term structural monitoring under limited accessibility conditions.

• Decomposition of temperature and displacement signals into daily and annual trend components, enabling a clearer interpretation of thermal effects on structural response.

• Identification and correction of the phase delay between temperature variations and structural displacement, improving the accuracy of the correlation between variables.

• Development of regression-based predictive models capable of estimating structural displacements from temperature measurements.

• Discussion of the potential application of Transfer Learning concepts to similar bridge structures, contributing to the development of scalable monitoring strategies for infrastructure networks.

Future work will focus on validating the proposed methodology using data from additional structures with similar typologies, as well as on integrating the developed predictive models into Transfer Learning approaches for large-scale monitoring of infrastructure networks.

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