



Modelling Climate Change Effects on Bridges in Portugal: A Framework for Temperature and Strain Analysis

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Abstract

Climate change poses increasing challenges to infrastructure, particularly bridges, requiring advanced adaptation and monitoring strategies. However, the lack of long-term monitoring data challenges the effective quantification of the impact of climate change on bridges. Therefore, this study presents a methodological framework for reconstructing temperature and strain measurements in a prestressed box girder bridge located in Portugal. The analysis integrates limited historical data from a structural health monitoring system and nearby weather stations, employing temperature downscaling models and advanced statistical techniques, including autoregressive model and long- and short-term time-series networks. The results demonstrate the effectiveness of these models and techniques in capturing temperature variations and assessing the influence of climatic conditions on structural deformations. This study is the beginning of broader analysis on the impact of climate change on concrete bridges.

Keywords: Bridge engineering; structural health monitoring, climate change; temperature downscaling, data analysis.

1 Introduction

Climate change and its associated challenges, particularly their impact on infrastructural assets, are critical issues for both present and future societies. The increasing frequency and intensity of catastrophic events worldwide in recent years highlight a trend that is expected to worsen in the

future [1]. These extreme events will impose additional stress on various infrastructure systems, including transportation networks (such as roads and railways), water supply, sanitation, flood control, and energy systems [2]. In particular, bridges are highly affected by climate change due to several factors that impact their structural integrity, safety, and lifespan [3].

Projected climate changes include a sustained increase in temperatures, fluctuations in relative humidity, shifts in precipitation patterns, rising sea levels, and changes in the intensity and frequency of extreme weather events such as heatwaves, droughts, floods, storms, and wildfires [1, 4–6]. The impacts of climate change cannot be considered uniform across a single country; rather, they are expected to vary by region and will depend on the effectiveness of adaptation and mitigation efforts [7]. When analysing climate change, the concept of non-stationarity—which suggests that past conditions and trends may no longer be reliable—along with the inherent uncertainty of climate projections, poses an increasing challenge to the traditional design and maintenance of infrastructure [8].

Predicting future climate projections is a complex task, characterized by significant uncertainty [9, 10]. Climate projections for a specific region or country are typically generated using general circulation models (GCMs) or regional climate models (RCMs). Figure 1 shows the global projections of the CO₂ for the commonly analysed representative concentration pathway (RCP) scenarios.

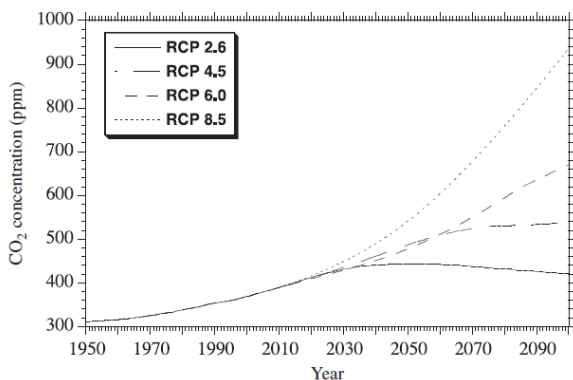


Figure 1. Projection of the CO₂ concentration for the main scenarios [11]

The four scenarios are defined in terms of RCPs, where the numerical values associated with each RCP represent the estimated radiative forcing values, expressed in W/m², by the year 2100 or at the point of stabilization thereafter, relative to pre-industrial levels [5, 10].

To achieve accurate predictions of future climate change variables, it is essential to have a reliable

approximation of past data. This is crucial not only for understanding the limitations of the model but also for improving the accuracy of future projections, despite the inherent uncertainties associated with climate variability [12].

A comprehensive dataset related to the bridge and its surrounding site is essential for this purpose. Structural health monitoring (SHM) systems play a crucial role in this context, serving as a tool to support the downscale climatic variables from a broader scale to the bridge site. Furthermore, these systems can be employed to evaluate how climate change may impact the bridge's characteristics and its components [13] in a long-term.

2 Framework for Data Reconstruction

This study introduces a framework for reconstructing historical temperature and strain monitoring data for a prestressed concrete bridge by integrating limited information from an SHM system and nearby weather stations.

The process begins with limited historical temperature and strain data from the SHM system, which is supplemented by weather station measurements to enhance data reliability. Statistical and machine learning models are then developed to downscale temperature measurements and reconstruct missing monitoring data, ensuring a more comprehensive dataset. These models are subsequently applied to estimate past temperature trends and strain variations while accounting for long-term environmental influences on the structure.

3 Case study

The bridge analysed in this paper as case study was completed in 1994 and is located in a mountainous area in the northeastern region of Portugal.

The structure is a continuous prestressed concrete box girder with a variable cross-section, reaching 42 meters in height near the piers. The bridge comprises three spans, with the central span measuring 115 meters in length and the two lateral spans each measuring 57.5 meters.

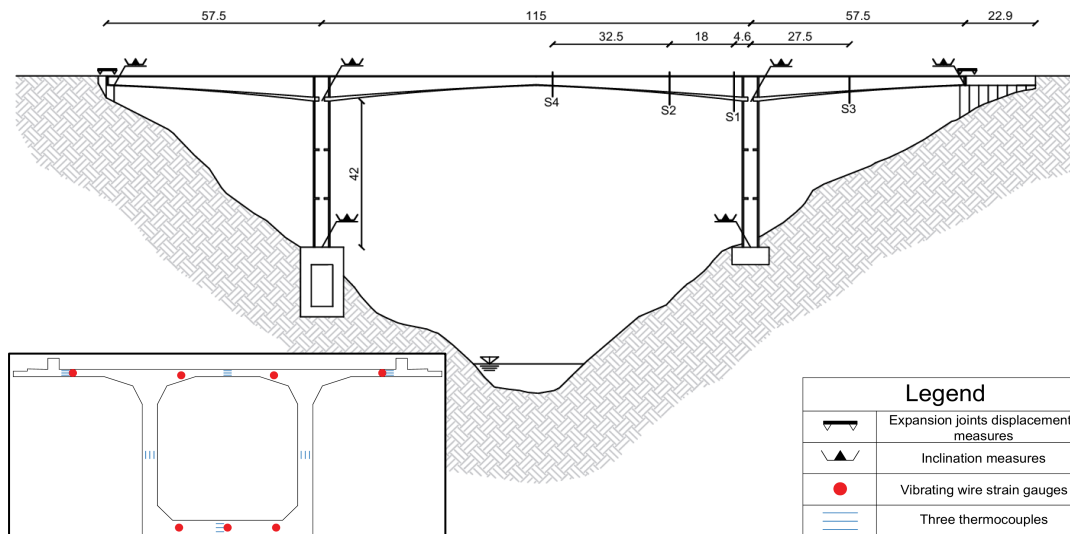


Figure 2. Schematic representation of the installed SHM system

3.1 Description of the SHM system

The SHM system implemented in the bridge comprises vibrating wire strain gauges and thermocouples embedded within the concrete during the construction phase. Additionally, external temperature sensors were included for monitoring relative humidity and temperature across various sections of the structure. These sensors were installed in four sections (S1, S2, S3, and S4), as depicted in Figure 2. The initial objective of the SHM system was to gain insights into the strain behaviour within the bridge girder, particularly during the early stages of its service life. This monitoring strategy aims to provide data on strain distribution and environmental effects, thereby supporting long-term structural performance assessment and maintenance strategies.

Due to the technological limitations at the time of the construction, data from the SHM system were manually collected by operators until 2011, with measurements taken approximately once per month. These periodic measurements were complemented by additional manual observations, including expansion joint displacements, as well as the inclination of both piers and girders. The specific locations at which the measurements were recorded are indicated in Figure 2.

For the purpose of studying impacts of climate change on the structural behaviour of the bridge,

the SHM was recently resumed over a one-year period, namely from March 2022 to March 2023. During this timeframe, data collection was conducted continuously and automatically, enabled by an upgraded acquisition system.

Additionally, new external temperature sensors were installed on the bridge to enhance environmental monitoring capabilities. Data acquisition focused exclusively on sections S3 and S4, providing a targeted analysis of the bridge's response under varying ambient conditions within these critical areas.

3.2 Weather stations data

To assess the normal behaviour of the structure and the typical variability of its parameters in the context of climate change, a minimum analysis period of 30 years is required [13]. To extend the time series of temperature data obtained through the SHM system, three weather stations located near the bridge (25 to 40 kilometres), were used. The dataset from the three weather stations includes different variables such as temperature, humidity, and solar insolation, all at the daily scale.

4 Temperature downscaling

4.1 Weather stations and SHM data

A comparison of temperature measurements from three weather stations, identified as 575, 633, and

637 (all located within 40 km of the bridge site), with the external bridge temperature recorded during the same year, in Figure 3, reveals similar seasonal patterns and daily fluctuations. The figure, which illustrates only the seasonal component obtained from the decomposition of the time series, demonstrates that the four temperature datasets exhibit only minor differences in their seasonal trends. These variations may be attributed to local climatic effects at the bridge site compared to the weather stations, highlighting the influence of site-specific factors on temperature measurements.

In Figure 4, a correlation analysis was conducted to identify variables recorded by the weather stations that influence the ambient temperature at the bridge site. As expected, the highest correlations are observed between the bridge temperatures and those recorded at the weather stations. Moreover, the relative humidity recorded at the weather stations also exhibits a notable negative correlation with bridge temperatures.

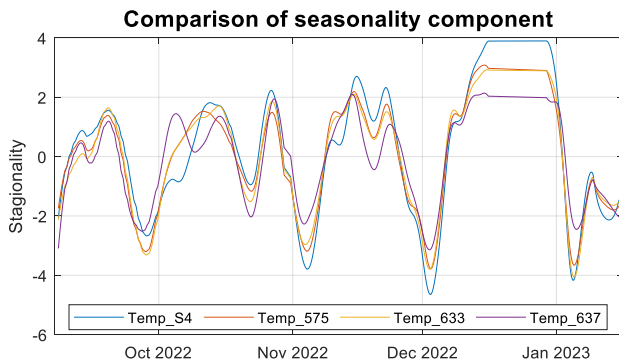


Figure 3. Overlap of weather station and bridge daily temperature measurements

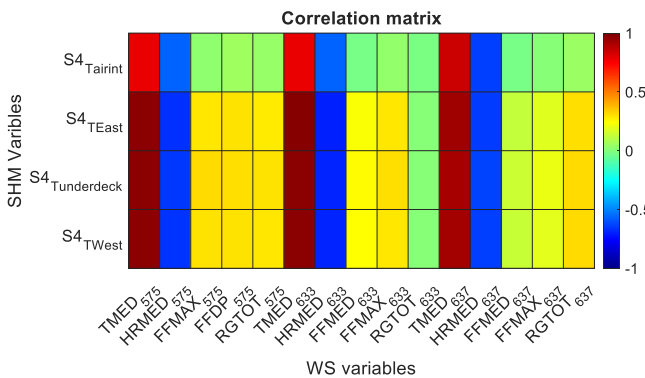


Figure 4. Correlations plots of the SHM and weather stations measurements

Based on data from the weather stations, a downscaling model was developed using regression algorithms to reconstruct past temperature trends at the bridge site.

4.2 Models for historical reconstruction

To identify the most suitable model for implementation, various mathematical and statistical models were tested and analysed. Six models were designed with incremental complexity to avoid unnecessary computational burden: multivariate linear regression; machine learning approaches, such as binary decision trees and gaussian process regression (GPR); feedforward neural networks (NN); long- and short-term time-series network (LSTNet); and seasonal autoregressive integrated moving average with exogenous variables (SARIMAX).

Table 1 presents a comparison of those models for temperature estimation. Various performance metrics were used, including root mean square error (RMSE), mean absolute error (MAE), median absolute error (MedAE), and the coefficient of determination (R^2). The results indicate that SARIMAX and LSTNet demonstrate the best performance in terms of RMSE and R^2 . However, when considering other metrics, both linear regression and GPR also yield promising results.

Table 1. Comparison analysis of different models

Type of Algorithm	RMSE	MAE	MedAE	R^2
Linear regression	1.89	1.43	1.11	0.92
Binary decision tree	2.27	1.75	1.34	0.89
GPR	1.91	1.41	1.06	0.92
NN	1.97	1.47	1.12	0.91
LSTNet	1.72	1.36	1.13	0.93
SARIMAX	1.76	1.35	1.06	0.93

4.3 Evaluation of statistical and neural network models

In this section, a comparison between the two best-performing models (SARIMAX and LSTNet) is conducted to evaluate two different

methodological approaches that give the best results. The first approach is based on statistical assessments and relies on autoregressive and seasonal parameters. The second approach is more complex and less interpretable, as it is based on mathematically defined parameters that are more difficult to characterize and involve a higher computational burden.

4.3.1 SARIMAX: statistical forecasting model

Autoregressive statistical models, including SARIMAX, are widely employed for damage identification in the SHM field, particularly for anomaly detection in time series data [14]. They enable one to understand the normal behaviour of the time series based on past patterns and dependence on external variables [14]. In this study, these models were applied to reconstruct the bridge's temperature behaviour.

The temperature and relative humidity, obtained from weather stations, were used as external inputs. The autoregressive terms in these models determine the current response as a linear combination of previous values. The moving average terms allow the estimation of the current response based on the previous errors. Additionally, seasonal dependencies were incorporated to better model the daily and yearly variations in the time series. Non-linearity was not considered in the model. The general equation of this model is defined in Eqn. (1):

$$\Phi(B)\Phi_s(B)(1-B)^d(1-B^s)^D y_t = c + \Theta(B)\Theta_s(B^s)\epsilon_t + \beta X_t \quad (1)$$

Where:

- $\Phi(B)$ denotes the autoregressive polynomial,
- $\Phi_s(B)$ are the seasonal autoregressive polynomial,
- $(1-B)^d$ corresponds to the non-seasonal differencing operator,
- $(1-B^s)^D$ denotes the seasonal differencing operator,
- $\Theta(B)$ represents the moving average polynomial,
- $\Theta_s(B^s)$ corresponds to the seasonal moving average polynomial,
- ϵ_t is a stochastic error term,

- X_t represents an exogenous regressor with its corresponding coefficient β ,
- c is an optional intercept term.

The selection of the model, as well as the subsequent parameter estimation, was defined by the Akaike information criterion.

4.3.2 LSTNet: for forecasting

Following the approach described by Silva et al. (2022) [15], the deep neural network employed is a long- and short-term time-series network (LSTNet), a complex model designed to capture long-term temporal patterns and accurately predict time-series behaviour (Figure 5). Integrating the classical autoregressive (AR) model, LSTNet linearly combines the neural network outputs with the AR component to generate the final predictions. The LSTNet architecture is composed of:

1. Convolutional layer, where w represents the mask width, traditionally used in video and image processing. However, in time-series applications, it helps streamline data complexity [16]. In this context, it serves two primary functions: first, it performs data reduction, which is particularly useful for managing extremely large time-series datasets; second, it captures local temporal dependencies facilitating the extraction of latent features from the input data.
2. Recurrent and recurrent-skip components operate in parallel over the outputs of the convolutional layer. These layers are designed to retain both short- and long-term seasonal information. Subsequently, the outputs, from both recurrent modules, are integrated through regression layers.
3. An AR model is constructed in parallel with the previous layers. While the deep network focuses on global predictions by capturing recurring patterns through nonlinear modelling, the autoregressive component provides a complementary approach for time-series forecasting.

Fully connected layer, used for predictions, integrating the outputs of the neural model with

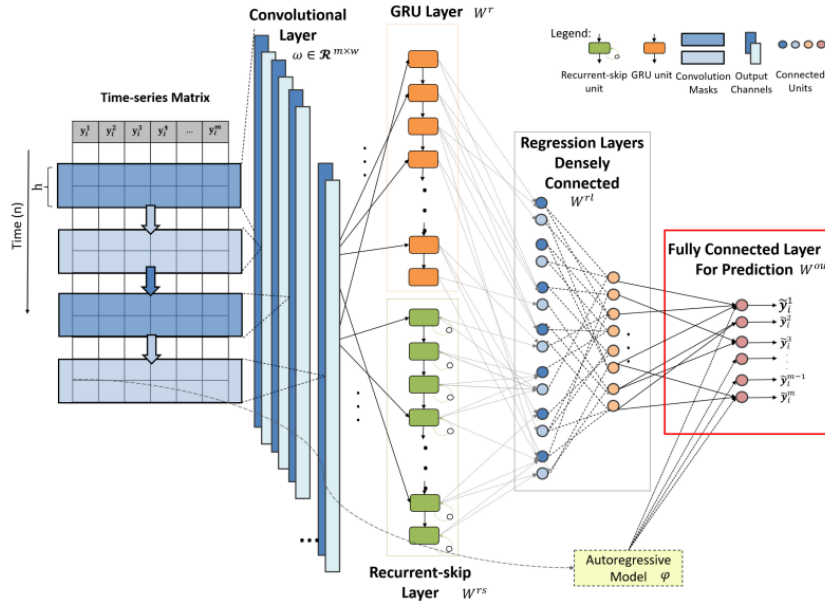


Figure 5. Overview of the LSTNet architecture [13]

the autoregressive component in a more direct manner. This layer enhances the overall performance by effectively coupling the outputs from the preceding layers.

4.3.3 Comparative performance analysis

The model comparison is based on error metrics for the test dataset and a graphical analysis of test residuals. Table 1 indicates that both models exhibit very similar performance, with LSTNet achieving a slightly lower RMSE of 1.72 compared to 1.76 for SARIMAX, and the same R^2 value of 0.93, suggesting a good prediction capability. However, SARIMAX demonstrates a lower MedAE, with a value of 1.06 compared to 1.13 for LSTNet, indicating fewer extreme errors. The MAE values are nearly identical, suggesting comparable average accuracy between the two models.

The comparison between the two models, in terms of residuals from the test dataset, is presented in Figure 6. The behaviour of the models is similar, with residuals for both mostly contained within the same range of $\pm 3^\circ\text{C}$, except for a few outliers that exceed these boundaries.

In both models, residual correlations are minimal, and the number of outliers remains relatively small. However, the LSTNet exhibits even fewer outliers

compared to SARIMAX. The SARIMAX shows higher residuals toward the end of the time series, whereas LSTNet demonstrates better predictive accuracy in this segment. Conversely, LSTNet presents higher residuals at the beginning of the series, which gradually decrease over time.

Overall, LSTNet offers a slight performance advantage. Despite its higher computational cost, this model is selected for the next evaluation.

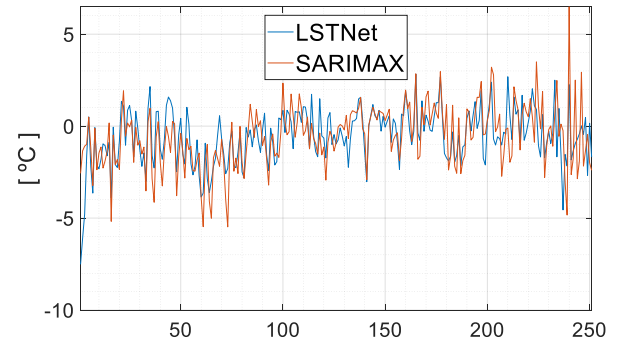


Figure 6. Residual comparison between SARIMAX and LSTNet

4.4 LSTNet-based temperature reconstruction

The overlap between the model and real observations during the monitoring year (2022–2023) is presented in Figure 7. In this figure, the time series is divided into training and test sets for

the LSTNet-based model. The training set demonstrates better performance compared to the test set; however, the differences are not significant enough to indicate overfitting. Additionally, the test set is affected by the absence of a considerable amount of data in its initial phase, which may have influenced the overall results.

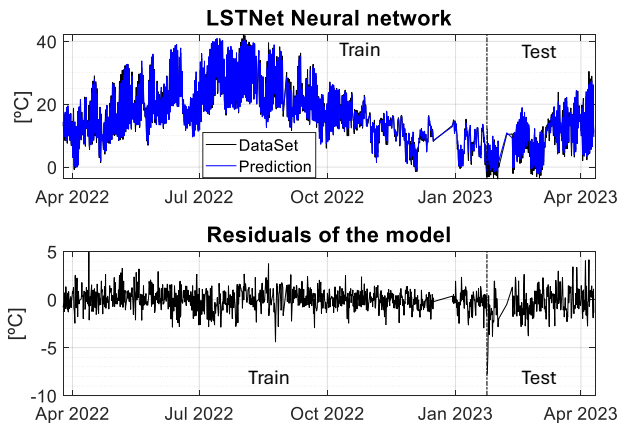


Figure 7. Results for training and test dataset for the LSTNet model. The upper part shows the overlap between the models and real measurements, the lower part shows the residuals

Figure 8 presents the complete reconstruction of the bridge's ambient temperature for the period from 2002 to 2023, obtained using the LSTNet model. The figure shows the overlap of manual measurements, represented by red dots, and the model's predictions. The differences between the manual and the modelled data are minimal.

It is important to highlight that, daily variations may exhibit some discrepancies compared to the model; however, the results indicate that the model can accurately predict seasonal temperature variations with minimal error.

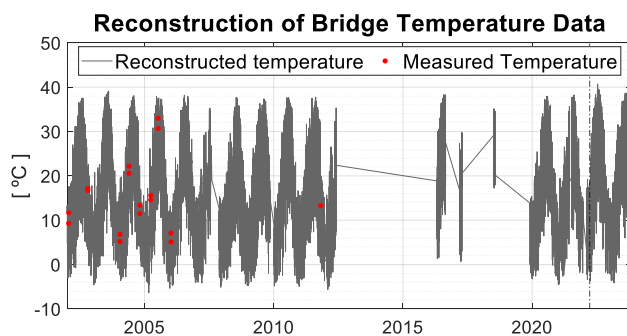


Figure 8. Reconstruct of bridge temperature air with LSTNet

5 Strain historical reconstruction

5.1 Correlation analysis between weather station and bridge strain data

A correlation analysis was conducted between temperature data from the weather stations and strain measurements observed at section S4 to identify external factors influencing strain behaviour in the bridge deck.

Figure 9 presents the correlation matrix between temperature data from the weather stations and strains in the monitored section. The results indicate a strong positive correlation between bridge strain and temperature measurements from all three weather stations, suggesting that as external temperatures increase, strains in the bridge deck also rise proportionally. Conversely, a significant negative correlation is observed between bridge strain and relative humidity, indicating that higher humidity levels are associated with a reduction in strains. However, other environmental variables do not show any substantial correlation with strain behaviour.

This analysis highlights temperature and humidity as primary environmental factors influencing strain behaviour, providing insights for constructing models sensitive to climate variations. Other variables are not considered as Figure 9 does not exhibit significant correlations with deck strains.

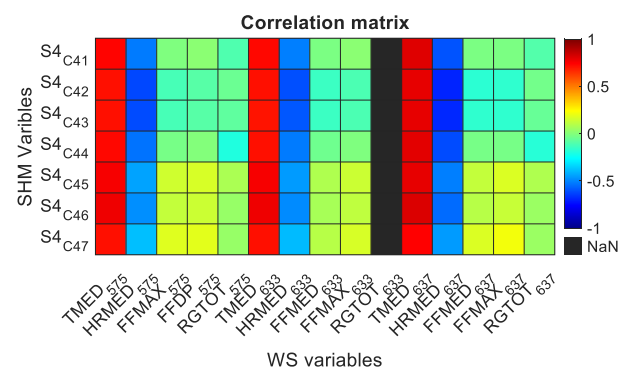


Figure 9. Correlation matrix between bridge strains and weather station variables

5.2 SARIMAX-based strain reconstruction

Strain variations in a structure can be influenced by temperature, humidity and potentially other factors that cannot be fully captured with the

available data, such as geotechnical movements, creep, shrinkage, and vehicle loads. The purpose of the statistical model is not to provide precise estimations of instantaneous deformation values, as this is inherently unfeasible due to the presence of unknown external variables and complex interactions with climatic conditions, which are subject to significant uncertainty.

Nevertheless, even when the exact values of the parameters cannot be determined, it remains possible to identify trends and assess their impact on the bridge's behaviour. The primary objective of the analysis is to characterize the broader and more complex patterns of temperature-driven deformation trends, even if instantaneous fluctuations are not explicitly captured.

Various models were compared to identify the optimal one with the lowest residuals. In this case, SARIMAX is used, using temperature data from weather stations. Figure 10 shows the estimated strain values in comparison with the observed measurements for one sensor located in section S4, along with the residuals for both the training and test datasets for one year of monitoring. The model does not perfectly predict strain behaviour, as residuals remain correlated, probably due to unmeasured external variables that were not considered in the model. Nonetheless, it achieves a prediction accuracy with an uncertainty margin of approximately 20% based on weather station data.

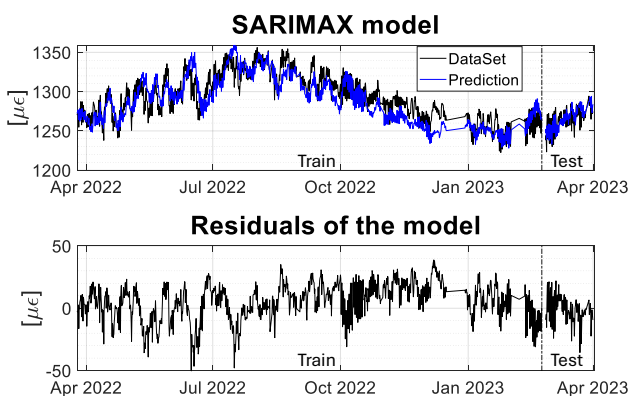


Figure 10. Results for training and test measurements for strain estimation

Figure 11 presents the reconstruction of historical strain data, where the SARIMAX model's reconstructed values are shown alongside

manually recorded strain measurements from 2002 to 2010. The distance between the two series probably indicates a significant influence of shrinkage effects on observed strain values, a factor that this model was unable to incorporate.

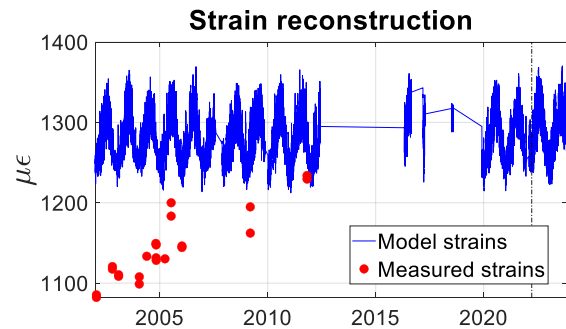


Figure 11. Comparison of the predicted strains and the manual measurements in section S4

In the subsequent phase of this study, the model will be adapted to account for shrinkage influences.

6 Conclusions

A framework was proposed for reconstructing past bridge temperature and strain data using data from nearby weather stations. The application of machine learning and statistical forecasting models, such as SARIMAX and LSTNet, have proven to be effective in capturing temperature trends and their influence on structural strains.

It was found that concrete shrinkage significantly affects the measurements obtained from strain sensors. This finding underscores the importance of accounting for this effect in strain measurements, particularly in this case study, and highlights its critical role in accurately reconstructing historical strain data.

7 Future developments

This study presents a data-driven framework for downscaling and reconstructing bridge temperature and strain measurements using data from weather stations and an SHM system. This analysis serves as an initial phase for future research focused on assessing the effects of climate change on concrete bridges. The models developed in this study will be applied to project temperature variations, incorporating different climate change scenarios.

8 Acknowledgments

The authors are grateful for the Foundation for Science and Technology's support through funding UIDB/04625/2020 from the research unit CERIS (DOI: 10.54499/UIDB/04625/2020).

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