Temperature Compensation in Vibration-Based Structural Health Monitoring Using Neural Network Regression

This is the final peer-reviewed author's accepted manuscript (postprint) of the following publication:

*Published Version:*
Temperature Compensation in Vibration-Based Structural Health Monitoring Using Neural Network Regression / Kamali, Soroosh; Marzani, Alessandro; Sciullo, Luca; Di Felice, Marco; Augugliaro, Giuseppe; Mennuti, Canio. - ELETTRONICO. - (2023), pp. 36-42. (Intervento presentato al convegno 2023 7th International Conference on System Reliability and Safety (ICSRS) tenutosi a Bologna, Italy nel 22/11/2023) [10.1109/ICSRS59833.2023.10381287].

*Availability:*
This version is available at: https://hdl.handle.net/11585/953402 since: 2024-01-18

*Published:*
DOI: http://doi.org/10.1109/ICSRS59833.2023.10381287

# Temperature compensation in vibration-based Structural Health Monitoring using neural network regression

Soroosh Kamali, Alessandro Marzani*
*Department of Civil, Chemical, Environmental and Materials Engineering*
*University of Bologna*
Bologna, Italy
soroosh.kamali2@unibo.it
alessandro.marzani@unibo.it

Luca Sciullo, Marco Di Felice
*Department of Computer Science and Engineering*
*University of Bologna*
Bologna, Italy
luca.sciullo@unibo.it
marco.difelice3@unibo.it

Giuseppe Augugliaro, Canio Mennuti
*Dipartimento Innovazioni Tecnologiche e Sicurezza degli Impianti*
*Prodotti ed Insediamenti Antropici, Laboratorio tecnologie innovative per la sicurezza*
*Centro Ricerche Monte Porzio Catone (RM)*
Rome, Italy
g.augugliaro@inail.it
c.mennuti@inail.it

***Abstract*—Vibration-based structural health monitoring (SHM) systems continuously estimate modal parameters to detect structural anomalies. The modal data corresponding to a healthy state are stored in a database during a training period, forming a baseline for comparison. However, variations in modal frequencies due to environmental and operational factors can lead to larger false positive rates and decrease the sensitivity of system to small damages, reducing the probability of damage detection. To mitigate these challenges, temperature compensation techniques are commonly employed to reduce variations in recorded modal data. In this paper, we propose a temperature compensation technique using neural network regression models. Unlike commonly used multivariate linear regression (MVLR), neural networks can capture the nonlinear relationship between temperature and modal frequencies effectively. The results of the numerical simulation in the present work demonstrate the superiority of the neural network-based compensation over the MVLR approach.**

***Index Terms*—Structural health monitoring, Anomaly detection, Temperature compensation, Neural network regression**

## I. INTRODUCTION

In vibration-based structural health monitoring (SHM) systems, continuous monitoring of modal parameters, such as modal frequencies, is performed using automated operational modal analysis (OMA) [1]. The frequencies corresponding to a healthy structural condition are stored in a database during a training period, creating a baseline for comparison. After the training phase, the SHM system enters the operational period, where it looks for anomalies. Anomalies are typically detected using a damage index (DI), a scalar quantity which measures the distance between the new frequency sample and the baseline. If the DI exceeds a certain threshold, an alert is triggered, indicating the presence of anomalous data [2].

However, variations in modal frequencies due to environmental and operational factors can lead to larger DI deviations from the threshold, increasing the risk of false positives or false alarms when the structure is actually healthy [3]. Additionally, these variations can also decrease the ability of the SHM system to reliably detect smaller damages in the structure, increasing the Minimum Detectable Damage (MDD) size [4].

To mitigate these issues, it is essential to reduce the variations of the recorded modal frequencies as much as possible, which leads to a decrease in the discussed risks. One of the most significant factors contributing to variations in modal frequencies is temperature fluctuations. Temperature variations affect materials, supports, and connections, resulting in direct effects on the natural frequencies of the structure [5]–[7].

To address the influence of temperature variations on modal frequencies, temperature compensation techniques are commonly employed, as also required by standards such as UNI/TR 11634, the Italian Guidelines for Structural Monitoring [8]. In this approach, thermocouples are installed on the structure to record temperature values corresponding to each sample of modal frequencies during the training phase. A regression model is then built for the dataset, with temperatures as the independent variables and modal frequencies as the target parameters. This regression model allows the reconstruction of modal frequencies, using corresponding temperature values as the input to the model. The temperature compensation is then performed on the modal frequencies by subtracting the reconstructed values from original frequencies [9], [10].

When the regression model is accurate, it is expected that the temperature-related variations of the compensated parameters are smaller than those of the original frequencies. This basically allows to better discriminate the variation of frequencies due to damage increasing thus sensitivity of the SHM system.

Most existing works employ multi-variate linear regression (MVLR) to build the regression model. However, the relationship between temperature and modal frequencies is highly nonlinear. Additionally, due to limitations in the number of thermocouples used in practice, there are usually only a few independent parameters available for regression. Consequently, MVLR may not fully exploit the potential of the available dataset for compensation purposes.

In this work, we propose a compensation technique that exploits neural network (NN) regression models to overcome the limitations of MVLR. Neural networks are capable of capturing complex nonlinear relationships between temperature and modal frequencies, making them well-suited for this task. Thus, using NN, the variations in modal frequencies are reduced more effectively compared to MVLR-based compensation. Consequently, the probability of damage detection is noticeably increased. The approach is investigated through a numerical truss example by considering the temperature variations and measurement noises. In this example, for three cases: (I) no compensation, (II) compensation using MVLR, and (III) compensation using NN, the resulting PODs are compared. Moreover, the effect of proper selection of independent parameters in the regression models are discussed.

## II. Temperature compensation using MVLR

Let $\mathbf{H}$ be the matrix representing the baseline modal frequencies of a healthy structure (training dataset), and $\mathbf{T}$ be the corresponding baseline temperatures.

*Step 1: Building the regression model*
First, a multi-variate regression model is constructed to simulate the relationship between $\mathbf{H}$ and $\mathbf{T}$. This regression model is represented by the coefficient matrix $\boldsymbol{\beta}$, usually obtained using the least squares method and by minimizing the error $\mathbf{E}$ of (1):

$$\mathbf{E} = \mathbf{H} - \boldsymbol{\beta}.\mathbf{T} \tag{1}$$

Here, $\boldsymbol{\beta}$ is a matrix containing the regression coefficients.

*Step 2: Frequency reconstruction*
For any frequency sample $\mathbf{f_n}$ from the baseline or test dataset with corresponding temperature vector of $\mathbf{t_n}$, the frequencies are reconstructed using the regression model. The reconstructed frequencies $\hat{\mathbf{f}}_n$ are given by:

$$\hat{\mathbf{f}}_n = \boldsymbol{\beta}.\mathbf{t}_n \tag{2}$$

It should be noted that $\mathbf{f_n}$ could be related to a healthy or damaged state of the structure.

*Step 3: Compensation*
With the reconstructed frequencies at hand, the temperature compensation is performed by subtracting the respective reconstructed frequencies from the original data and adding the mean of the baseline modal frequencies:

$$\mathbf{f}_n^c = \mathbf{f}_n - \hat{\mathbf{f}}_n + \mu[\mathbf{H}] \tag{3}$$

If we use (3) for the baseline frequencies $\mathbf{H}$, the baseline for the compensated frequencies $\mathbf{H}^c$ can be obtained as follows:

$$\mathbf{H}^c = \mathbf{H} - \hat{\mathbf{H}} + \mu[\mathbf{H}] \tag{4}$$

## III. Temperature compensation using neural network regression

Neural network (NN) regression is a machine learning technique which finds a model to predict target parameters having the independent features.

The NN concept centers around the organization of input, hidden, and output layers, each comprising neurons. Specifically, the number of neurons in the input and output layers corresponds to the number of independent and target variables, respectively. However, the number of neurons in the hidden layers is a hyperparameter decided based on the complexity of the problem [11].

Within each layer, individual neurons derive their values through a weighted sum of the preceding layer neurons, with the addition of a bias term. These computed values then undergo a non-linear "activation function," introducing nonlinearity into the estimations. Sigmoid, ReLU (Rectified Linear Unit), tangent, and hyperbolic tangent are popular activation functions [12].

The training phase begins with "forward propagation," where computations cascade through the layers until arriving at the output layer providing predictions for the target variables. These predictions are then compared to the actual values for error assessment. Subsequently, during "backward propagation," weight coefficients and biases are adjusted to minimize the prediction error. Hyperparameters such as gradient, step, and loss tolerances and iteration limit correspond to this optimization problem. Once the optimal weights and biases are determined, the NN model is ready for making predictions [12].

In the present work, we propose using NN to build a regression model ($mdl$) between the temperatures as the independent, and the modal frequencies as the target parameters on the baseline dataset. Then, the reconstructed frequencies ($\hat{\mathbf{f}}_n$) are obtained from the prediction of $mdl$ having the corresponding temperature values $\mathbf{t_n}$:

$$\hat{\mathbf{f}}_n = predict(mdl, \mathbf{t}_n) \tag{5}$$

Then, the frequencies compensated for temperature variations can be calculated using (3) and (4).

In the present paper, the built-in $MATLAB$ function `Mdl = fitrnet(X,Y)` has been used to construct the neural network regression model with `X` and `Y` as independent and target variables, respectively [13]. This function provides the possibility to adjust different hyperparameters mentioned above.

To predict the target value on a given input, the built-in function `yfit = predict(Mdl,X)` is used. This function computes the prediction `yfit` using the input `X`, employing the NN regression model `mdl`.

For the case study investigated in this work, the neural network model is visually depicted in Fig. 1. The input layer comprises three neurons, corresponding to the three temperature measurements, while the output layer consists of five neurons, representing the five frequencies. Furthermore, the intermediate hidden layer consists of ten neurons. The utilized hyperparameters are detailed in Tab. I.

TABLE I
NEURAL NETWORK REGRESSION HYPERPARAMETERS.

| Hyperparameter | Value |
|---|---|
| Layer size | 10 |
| Iteration limit | $10^3$ |
| Gradient tolerances | $10^{-6}$ |
| Step tolerances | $10^{-6}$ |
| Loss tolerances | $10^{-6}$ |
| Regularization term strength | 0 |
| Standardization | Off |
| Activation function | ReLU |

## IV. DAMAGE INDEX

A damage index (DI) is considered based on the modal frequencies which could be non-compensated or compensated for temperature, the latter using MVLR or NN. First, the baseline matrix $\mathbf{H}$ is considered as the training database, and its mean value vector and covariance matrix are calculated as $\mu[\mathbf{H}]$ and $\mathbf{S}$, respectively.

Then, for each frequency sample $\mathbf{f}_n$, a scalar damage index $DI_n$ is computed using the Mahalanobis distance [2], [14] as:

$$DI_n = \sqrt{(\mathbf{f}_n - \mu[\mathbf{H}])^T \mathbf{S}^{-1} (\mathbf{f}_n - \mu[\mathbf{H}])} \tag{6}$$

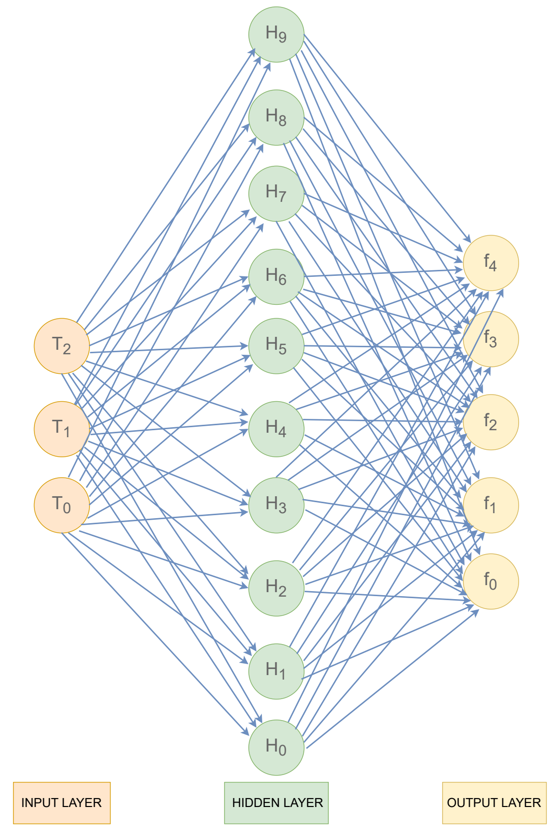


Fig. 1. The NN regression model of the current case study.

The Mahalanobis distance is a scalar indicating the distance between a sample point $\mathbf{f}_n$, and a probability distribution $Q(\boldsymbol{\mu}, \mathbf{S})$ in a multi-dimensional space, taking into account the correlation of the data.

For instance, in Fig. 2a, the DIs are calculated for two years. In the first year (blue dots), the structure is healthy and is used as the baseline $\mathbf{H}$ matrix. In the second year (red dots), the structure is damaged and the DIs are computed with respect to $\mathbf{H}$.

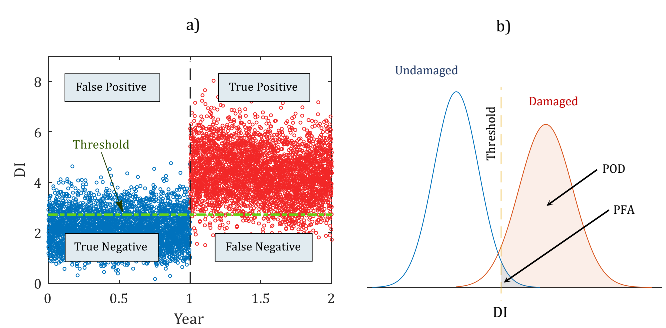


Fig. 2. Classification based on an alarm threshold: a) different outcomes; b) PFA and POD from the probability density functions.

It is worth mentioning that in (6), if $\mathbf{f}_n^c$ and $\mathbf{H}^c$ are used instead of $\mathbf{f}_n$ and $\mathbf{H}$, respectively, the calculated DIs will be based on the temperature compensated frequencies.

Both MVLR or NN can be used for compensation and DI calculation.

## V. PFA, POD, AND ALARM THRESHOLD

The alarm threshold ($\tau$) is a value defined on the DIs which classifies the dataset into two categories of healthy (negative) for $DI \leq \tau$, and damaged (positive) for $DI > \tau$. For instance, the green horizontal dashed line represented in Fig. 2a is the alarm threshold on the introduced dataset.

In a supervised scenario where the damage is known, the number of healthy samples with $DI > \tau$ (false positives) is taken as $FP(\tau)$ (Fig. 2a, top-left quarter), the number of $DI < \tau$ (true negatives) is taken as $TN(\tau)$ (Fig. 2a, bottom-left quarter), the number of damaged samples with $DI > \tau$ (true positives) is taken as $TP(\tau)$ (Fig. 2a, top-right quarter), and the number of $DI < \tau$ (false negatives) is taken as $FN(\tau)$ (Fig. 2a, bottom-right quarter).

Therefore, given a $\tau$ value, we can calculate the probability of false alarm $PFA(\tau)$ and the probability of damage detection $POD(\tau)$ as follows:

$$\begin{aligned} PFA(\tau) &= \frac{FP(\tau)}{FP(\tau)+TN(\tau)} \\ POD(\tau) &= \frac{TP(\tau)}{TP(\tau)+FN(\tau)} \end{aligned} \tag{7}$$

Both $PFA(\tau)$ and $POD(\tau)$ are visually illustrated in Fig. 2b, showcasing the distributions of DIs for the healthy and damaged scenarios. It can be seen that having a threshold, if the variations of the DIs decrease, the POD increases, and the PFA decreases.

In this study, we utilize the $PFA$ to establish the alarm threshold for the SHM system [4], [15]. For this purpose, we take the DI corresponding to $PFA = 0.05$ on the baseline DI dataset as the alarm threshold. Such procedure can be performed on compensated or non-compensated datasets.

## VI. PROCEDURE

The process of temperature compensation used in this work can be summarized as follows:

*I: For the healthy structure*

1) Collect modal frequencies of the healthy structure through operational modal analysis and simultaneously, record corresponding temperature measures. Consider a period of the healthy frequencies as the training or baseline period, preferably covering one year to ensure a well-trained regression model in the next steps. Keep the remaining of the healthy samples as the test dataset.
2) Perform a correlation analysis between frequency and temperature variations to select thermocouples with high correlation as independent variables for the regression model.
3) Build regression models (MVLR or NN) with frequencies as the target and the chosen temperatures as independent parameters on the baseline.
4) Use the regression model to compensate for temperature fluctuations in the baseline frequencies. Thus, the baseline of the frequencies compensated for temperature is obtained.
5) Calculate the DI for the baseline frequencies compensated for temperature fluctuations by computing the Mahalanobis distance. Determine the threshold value ($\tau$) for the DI corresponding to a PFA of 5%.
6) For the healthy test dataset, apply the regression model for compensation and calculate the DIs. Use $\tau$ and verify that the PFA obtained from the test dataset is close to 5% to assess the robustness of the regression model.

*II: For the damaged structure (supervised scenario)*

1) In the framework of a supervised approach, use for instance a calibrated finite element model (FEM) to simulate a damage scenario.
2) Use a temperature history, perhaps covering one year of time, and properly apply it to the FEM model for the computation of the temperature dependent modal frequencies; introduce a noise with a given standard deviation on such frequencies.
3) Calculate the DIs of the damaged samples using the Mahalanobis distance of (6) and compute the POD for the calculated threshold value ($\tau$).
4) Repeat the procedure with different regression models or combinations of independent/target variables and compare the resulting PODs.

In the next section, this procedure is applied to a numerical example and the performances of different regression models for temperature compensation are compared.

## VII. NUMERICAL EXAMPLE

A 9-element plane truss composed of steel elements with properties defined at a reference temperature of 20°C is analyzed. The truss has a Young's modulus ($E_0$) of 200 GPa, a cross-sectional area ($A$) of $0.0025\ m^2$, and a material density ($\rho$) of 7850 $kg/m^3$ (Fig. 3). Using finite element model and solving eigenvalue problem, the first five modal frequencies of the truss are calculated as $f_1 = 36.71$, $f_2 = 78.91$, $f_3 = 82.00$, $f_4 = 145.97$, and $f_5 = 219.22$ Hz.

Three temperature distributions $T_1$, $T_2$, and $T_3$ are created, and for each, seasonal ($T^Y$), daily ($T^D$), and random ($T^R$) variations for a three-year period are considered (Fig. 4). Ten temperature samples per day are simulated, resulting in a total of 3650 samples per year for each distribution. The relations used to build the temperature distributions are presented in Tab. II, in which $i = 1$ to 10950 is the sample number, $N_Y = 3650$ is the number of samples per year, and $N_D = 10$ is the number of samples per day.

The temperature effect on the truss structure is then incorporated at all elements using a non-linear temperature-dependent Young's modulus, as described by the following equation [16]:

$$\begin{aligned} E(T) = E_0[1 - 0.005(T-20)^{(-0.01T)} \\ +0.01\ rand[\mathcal{N}(0,1)]] \end{aligned} \tag{8}$$

TABLE II
THE SEASONAL, DAILY, AND RANDOM TEMPERATURE VARIATIONS OF THE THREE TEMPERATURE MEASURES.

| | $T_1$ | $T_2$ | $T_2$ |
|---|---|---|---|
| $T^Y$ | $T_1^Y\ (i) = 20\ +\ 25\ \sin(2\pi i/N_Y)$ | $T_2^Y\ (i) = 15\ +\ 20\ \sin(2\pi i/N_Y)$ | $T_3^Y\ (i) = 17\ +\ 25\ \sin(2\pi i/N_Y\ + 2/3)$ |
| $T^D$ | $T_1^D\ (i) = 20\ \sin(2\pi i/N_D)$ | $T_2^D\ (i) = 16\ \sin(2\pi i/N_D)$ | $T_3^D\ (i) = 20\ \sin(2\pi i/N_D\ + 2\pi/3)$ |
| $T^R$ | $T_1^R\ (i) = 5\ rand[\mathcal{N}(0,1)]$ | $T_2^R\ (i) = 2\ rand[\mathcal{N}(0,1)]$ | $T_3^R\ (i) = 8\ rand[\mathcal{N}(0,1)]$ |

where $T = (T_1 + T_2 + T_3)/3$. Fig. 5 illustrates the variations of the Young's modulus of the elements with respect to the mean temperature value $T$.

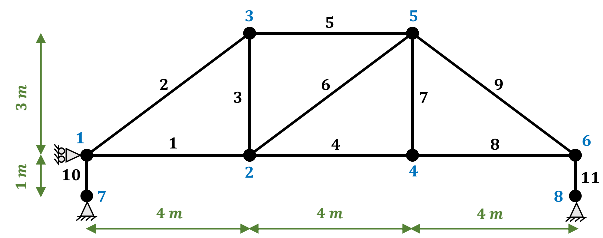


Fig. 3. The truss under investigation.

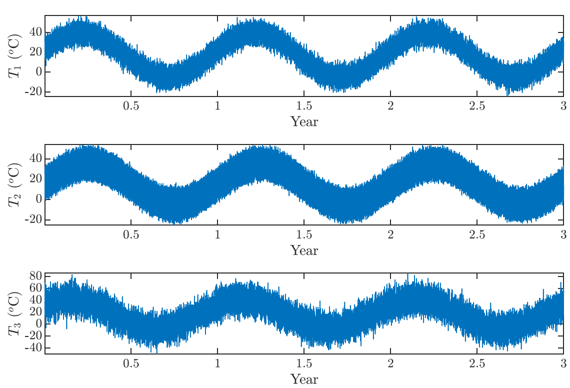


Fig. 4. The simulated temperature variations for three years.

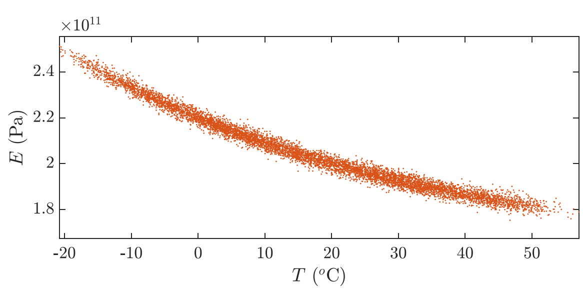


Fig. 5. The variations of element Young's modulus for the healthy dataset using (8).

For the healthy structure, the first five modal frequencies are computed over the first 7300 temperature samples (two-year duration). The baseline frequency matrix **H** is then constructed using the first 3650 samples as the healthy training, and the second 3650 samples are considered as the healthy test dataset.

Then, a damage is applied on element 1 as 16% reduction in the cross-sectional area, and the last 3650 temperature samples are used to obtain the first five modal frequencies in the presence of this damage scenario. All frequencies (healthy and damaged) are then contaminated by 1% noise to simulate typical noise levels in SHM systems [17] (Fig. 7).

Next, the frequencies without tempearature compensation are used to calcualte the DIs, visualized in Fig. 6. In this scenario, a threshold of $\tau = 3.314$ was obtained corresponding to a $PFA = 0.05$ on the baseline, resulting in a $PFA$ of 0.054 on the test dataset, demonstrating the robustness of the damage index. However, a $POD$ of 0.5252 is obtained, indicating a performance no better than random guessing.

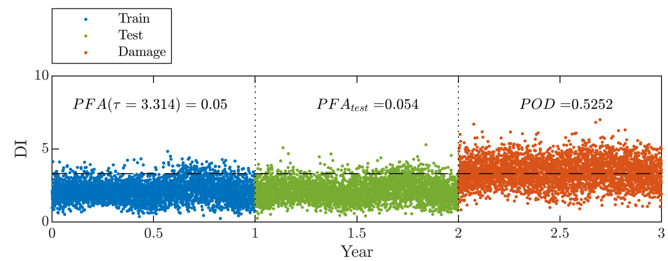


Fig. 6. The DI variations with no temperature compensation.

Next, temperature compensation is performed on the frequencies. For this purpose, four different combinations of independent parameters, namely $T_1$, $T_1 - T_2$, $T_2 - T_3$, and $T_1 - T_2 - T_3$ are considered for the regression models. Temperature compensation is then performed using both MVLR and NN regression with the first five modal frequencies as the target variables. The hyperparameters used in constructing the NN regression model are introduced in Tab. I.

For each regression type (MVLR or NN), and each combination of independent parameters ($T_1$, $T_1 - T_2$, $T_2 - T_3$, or $T_1 - T_2 - T_3$), the DIs are computed and the alarm thresholds $\tau$ associated with a $PFA$ of 0.05 are determined on the baseline.

Figs. 8, 9, 10, and 11 represent the DIs considering only $T_1$, $T_1 - T_2$, $T_2 - T_3$, and $T_1 - T_2 - T_3$, respectively, as independent parameters in the regression models. In each plot, the first row shows the DIs calculated using MLVR compensation, whereas in the second row, the NN regression model was used. Tab. III summarizes the resulting $POD$s for different scenarios.

TABLE III
THE POD RESULTS FOR DIFFERENT REGRESSION MODELS AND INDEPENENT PARAMETERS.

| | $T_1$ | $T_1$ and $T_2$ | $T_2$ and $T_3$ | $T_1$, $T_2$, and $T_3$ |
|---|---|---|---|---|
| MVLR | 0.7595 | 0.7608 | 0.7033 | 0.7581 |
| NN | 0.9293 | 0.8666 | 0.8027 | 0.8923 |

Compared to the case without temperature compensation (Fig. 6), using MVLR increased the $POD$ values to 0.7595,

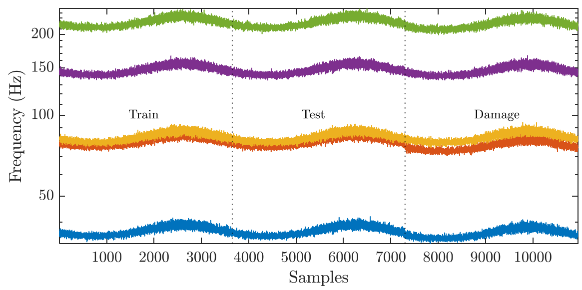


Fig. 7. Pseudo frequencies of the healthy (first and second years) and the damaged (third year) structure for the damage on element 1, as 16% reduction in the cross-sectional area.

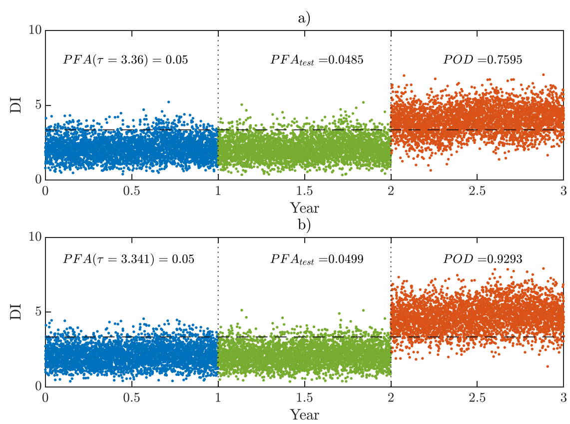


Fig. 8. The DI variations using only $T_1$ as the independent parameter with: a) MVLR compensation; b) NN compensation.

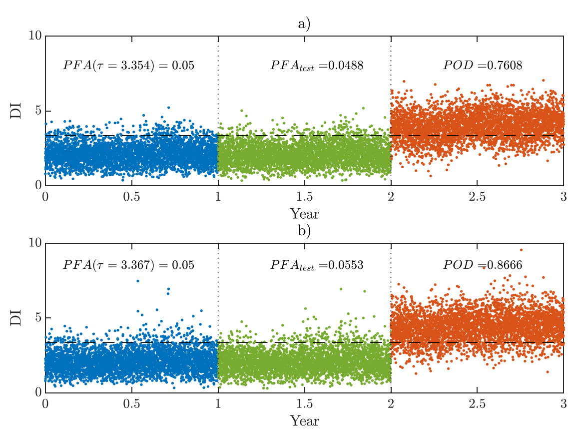


Fig. 9. The DI variations using $T_1$, $T_2$ as the independent parameters with: a) MVLR compensation; b) NN compensation.

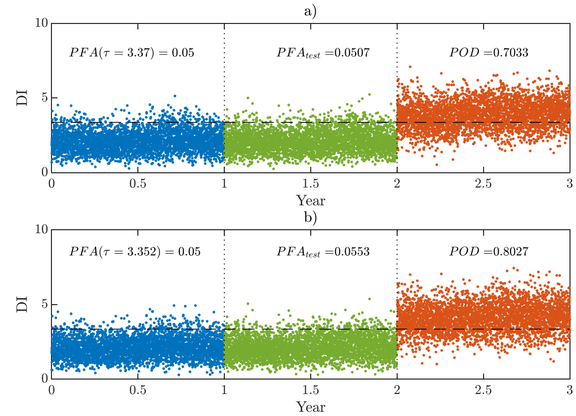


Fig. 10. The DI variations using $T_2$ and $T_3$ as the independent parameters with: a) MVLR compensation; b) NN compensation.

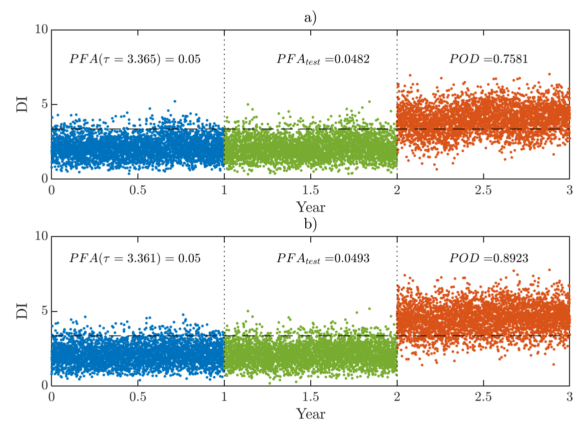


Fig. 11. The DI variations using $T_1$, $T_2$ and $T_3$ as the independent parameters with: a) MVLR compensation; b) NN compensation.

0.7608, 0.7033, and 0.7581 for the four temperature combinations, respectively. These results demonstrate the effectiveness of temperature compensation in enhancing the damage detection capability of the system with MVLR.

Similarly, when utilizing NN for temperature compensation, higher $POD$ values were achieved, specifically 0.9293, 0.8666, 0.8027, and 0.8923 for the four combinations mentioned, respectively.

The findings clearly indicate that using NN for temperature compensation is more effective in increasing the $POD$ while maintaining a low $PFA$. For instance, considering only $T_1$ as the independent parameter resulted in a $POD$ of 92%, whereas with the use of MVLR, the $POD$ was 76%.

Altogether, both MVLR and NN compensation showed higher $POD$ values in cases involving $T_1$ compared to scenarios that only included $T_2$ and $T_3$. To further explain this observation, a correlation coefficients matrix between the baseline frequencies and the temperatures was calculated (Fig. 12).

Analyzing this matrix reveals that $T_1$ exhibits the strongest correlation (more than 95%) with all modal frequencies.

Tab. II confirms this observation where $T_1$ has the largest constants and coefficients, making it the most effective factor in computing $T$ in (8). Moreover, $T_2$ also shows a noticeable correlation with frequencies (more than 85%), while weaker than that of $T_1$. However, $T_3$ demonstrates less correlation with the frequencies (more than 62%). This could be due to the phase shift in $T_3^Y$ and $T_3^D$ (Tab. II), leading to a smaller contribution to $T$ in (8) compared to the in-phase temperatures $T_1$ and $T_2$.

This observation implies the importance of preliminary study on the SHM system to identify which independent parameters significantly affect the variations in target frequencies to be used for temperature compensation.

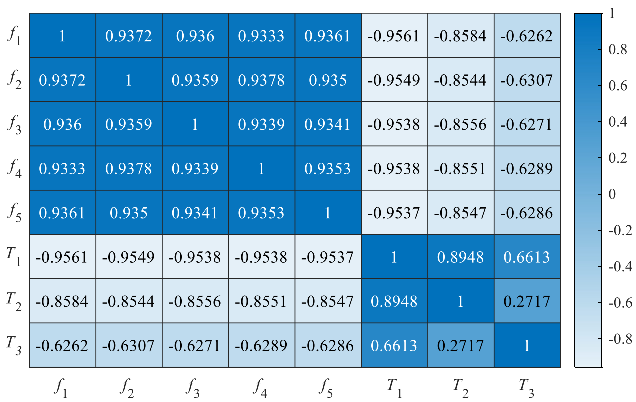


Fig. 12. Correlation coefficients matrix of the independent and target parameters.

## VIII. Conclusions

In this work, we addressed the challenges of SHM systems caused by variations in modal frequencies due to environmental and operational factors, which may lead to false positives and reduce sensitivity to small damages. To mitigate these issues, we proposed a temperature compensation technique using neural network regression models, which have the ability to capture complex nonlinear relationships between temperature and modal frequencies. Through numerical validation, we demonstrated the superiority of the neural network-based compensation technique over the multi-variate linear regression approach. The neural network regression significantly reduced temperature-induced variations in modal frequencies, resulting in a significant improvement in the probability of detecting structural damages. Moreover, we investigated the importance of preliminary correlation analysis between the independent and target parameters, to chose effective features for temperature compensation.

## Acknowledgment

The presented work has been partially supported by the project "DS2: Digital Smart Structures", funded by INAIL (National Institute for Insurance against Accidents at Work), BRIC 2021.

## References

[1] R. Brincker and C. Ventura, *Introduction to operational modal analysis*. John Wiley & Sons, 2015.

[2] A.-M. Yan, G. Kerschen, P. De Boe, and J.-C. Golinval, "Structural damage diagnosis under varying environmental conditions—part i: A linear analysis," *Mechanical Systems and Signal Processing*, vol. 19, no. 4, pp. 847–864, 2005.

[3] Y. Xia, B. Chen, S. Weng, Y.-Q. Ni, and Y.-L. Xu, "Temperature effect on vibration properties of civil structures: a literature review and case studies," *Journal of civil structural health monitoring*, vol. 2, no. 1, pp. 29–46, 2012.

[4] S. Kamali, S. Quqa, A. Palermo, and A. Marzani, "An approach to define the minimum detectable damage and the alarm thresholds in vibration-based shm systems," in *XII International Conference on Structural Dynamics (EURODYN)*, Delft, the Netherlands, 2023.

[5] X. Hua, Y. Ni, J. Ko, and K. Wong, "Modeling of temperature–frequency correlation using combined principal component analysis and support vector regression technique," *Journal of Computing in Civil Engineering*, vol. 21, no. 2, pp. 122–135, 2007.

[6] M. A. Wahab and G. De Roeck, "Effect of temperature on dynamic system parameters of a highway bridge," *Structural Engineering International*, vol. 7, no. 4, pp. 266–270, 1997.

[7] A. Kita, N. Cavalagli, and F. Ubertini, "Temperature effects on static and dynamic behavior of consoli palace in gubbio, italy," *Mechanical Systems and Signal Processing*, vol. 120, pp. 180–202, 2019.

[8] Ente nazionale italiano di unificazione, *UNI/TR 11634: 2016: *Linee guida per il monitoraggio strutturale*. UNI, 2016.

[9] F. Magalhães, Á. Cunha, and E. Caetano, "Vibration based structural health monitoring of an arch bridge: From automated oma to damage detection," *Mechanical Systems and signal processing*, vol. 28, pp. 212–228, 2012.

[10] Z. Wang, D.-H. Yang, T.-H. Yi, G.-H. Zhang, and J.-G. Han, "Eliminating environmental and operational effects on structural modal frequency: A comprehensive review," *Structural Control and Health Monitoring*, vol. 29, no. 11, p. e3073, 2022.

[11] I. H. Sarker, "Machine learning: Algorithms, real-world applications and research directions," *SN computer science*, vol. 2, no. 3, p. 160, 2021.

[12] S.-C. Wang and S.-C. Wang, "Artificial neural network," *Interdisciplinary computing in java programming*, pp. 81–100, 2003.

[13] The MathWorks Inc., "Matlab version: R2022a," *Natick, Massachusetts, United States*, 2022.

[14] P. C. Mahalanobis, "On the generalised distance in statistics," in *Proceedings of the national Institute of Science of India*, vol. 12, pp. 49–55, 1936.

[15] D. Toshkova, M. Asher, P. Hutchinson, and N. Lieven, "Automatic alarm setup using extreme value theory," *Mechanical Systems and Signal Processing*, vol. 139, p. 106417, 2020.

[16] M. Seif, L. Choe, J. Gross, W. E. Luecke, J. A. Main, D. McColskey, F. Sadek, J. M. Weigand, and C. Zhang, *Temperature-dependent material modeling for structural steels: formulation and application*. US Department of Commerce, National Institute of Standards and Technology, 2016.

[17] M. Jahangiri, A. Palermo, S. Kamali, M. A. Hadianfard, and A. Marzani, "A procedure to estimate the minimum observable damage in truss structures using vibration-based structural health monitoring systems," *Probabilistic Engineering Mechanics*, vol. 73, p. 103451, 2023.