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Determining the temperature using natural frequencies and artificial intelligence

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Abstract. *The current paper explores a novel approach for determining temperature variations by integrating the modal parameters and AI techniques. The research focuses on the development of a comprehensive dataset for training an AI model encompassing an analytical method that considers thermal conditions and natural frequencies. Traditional methods of temperature measurement, like infrared and platinum resistance thermometers, often face limitations in terms of accuracy, especially in complex or dynamic environments having an uncertainty of ±3.6 °C [1], respectively ±0.2 °C [2]. In this study, we propose a methodology that harnesses the inherent relationship between axial loads caused by temperature variations and the change in natural frequencies of a double clamped steel beam. The measured natural frequency data is collected and fed into the AI model, specifically, for a robust temperature estimation, obtaining a maximum predicted temperature deviation of 0.386 °C.*

Keywords: *temperature, natural frequency, artificial intelligence, finite element method, thermal condition*

1. Introduction

Environmental variations can modify the modal characteristics of structures [3], which can result in a correlation between the natural frequencies and temperature. The effect of temperature is considered by most researchers as the most significant in the change in the dynamic behavior of the structure rigidly fixed at the ends [4 - 6]. Its effect on the natural frequencies of metallic structures is presented in [7, 8]. In the work [9], a study was carried out in which the influence of the temperature upon the natural frequencies of a simply supported reinforced concrete beam is analyzed, and the effect of the temperature variation is quantified.

In papers [10, 11] the authors found that the variations in natural frequencies caused by the temperature changes were comprised of between 4.7 and 6.6 %, which was more significant than the changes caused by an artificial cut.

The current study proposes a machine-learning model that can predict environmental temperature changes by considering the natural frequency shift due to temperature changes in double-clamped steel beams. The changes in the eigenfrequencies are determined by the axial forces developed by the fixed expanding structure [12]. The considered structure is a double-clamped steel beam, with its properties denoted in Table 1.

Table 1. Physical-mechanical properties of the material

Mass density ρ [kg/m^3]	Young modulus E [N/m^2]	Poisson ratio υ [-]	Thermal expansion coefficient α [mm/°C]
7850	$2.06 \cdot 10^{11}$	0.28	0.015

The considered beam's geometry and dimensions in mm are presented in Fig 1.

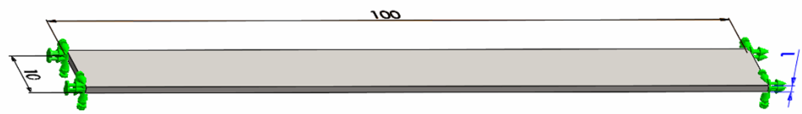


Figure 1. Double-clamped beam

By considering a reference temperature T_{ref} which is increased with ΔT, the internal force is given by [13]:

$$P(T) = \alpha \cdot E \cdot A \cdot \Delta T \tag{1}$$

where A is the cross-section of the beam, E is the elasticity modulus and α is the thermal expansion coefficient.

The characteristic equation for a beam fixed at both ends is [10]:

$$\zeta \sin \zeta + 2 \cos \zeta - 2 = 0 \tag{2}$$

The critical forces P_{cr} and critical temperature T_{cr} can be found as [10]:

$$P_{cr-i} = \frac{\zeta_i^2 E \cdot I}{L^2} \tag{3}$$

and

$$T_{cr-i} = T_{ref} + \Delta T_{cr} = T_{ref} + \frac{P_{cr-i}}{\alpha \cdot E \cdot A} \tag{4}$$

By applying the transcendental Equation (5), the values for the first six bending vibration modes are obtained [10]:

$$1 + \cos\lambda \cdot \cosh\lambda = 0 \tag{5}$$

For a compression load scenario with fixed-fixed ends, when ζ_i is not equal to λ_i, the natural frequencies can be calculated using Equation (6) [10].

$$f_i(P) = f_{ref-i}\sqrt{1 - \frac{P}{P_{cr-i}}} \tag{6}$$

The mathematical equation representing the frequency change due to temperature variation is derived by inserting Equations (1) and (3) into Equation (6), resulting in [10]:

$$f_i(T) = f_{ref-i}\sqrt{1 - \frac{\alpha A(T - T_{ref})L^2}{I\zeta_i^2}} = f_{ref-i} \cdot \kappa_i(T) \tag{7}$$

where $k_i(T)$ is the temperature adjustment coefficient.

For a reference temperature T_{ref}, the first six buckling eigenvalues ζ_i, the bending vibration eigenvalues λ_i critical force P_{cr}, and critical temperature T_{cr} values for the double-clamped beam are shown in Table 2.

Table 2. The first six eigenvalues, critical forces, and temperatures

Buckling mode i	Eigenvalue ζ_i	Eigenvalue λ_i	Critical force P_{cr-i} [N]	Critical temperature T_{cr-i} [°C]
1	6.283185307	4.7300407	6.777128355	22.28607549
2	8.986818916	7.8532046	1386.430028	80.52385089
3	12.56637061	10.9956078	2710.851342	136.4301959
4	15.45050367	14.1371654	4097.993428	194.9841042
5	18.84955592	17.2787596	6099.41552	279.4679409
6	21.80824332	20.4203522	8164.457682	366.6373019

Applying the described method, a database consisting of the Relative Frequency Shifts (RFS's) is generated using Equation 8, by considering the reference temperature T_{ref}=22°C and the iterative temperature increase of Δt=2°C, until T_{final}=50° thus obtaining 141 scenarios including the reference temperature where the RFS values for all modes are zero.

$$RFS_i = \frac{f_{ref-i} - f_i(T)}{f_{ref-i}} \tag{8}$$

2. Training the ANN

A robust ANN for predictive analysis is modeled using the nntool with Bayesian regularization through MATLAB software with a focus on predicting temperatures using the RFS data which was inserted as input [11]. The Bayesian regularization approach is used to prevent the overfitting phenomenon and to enhance the network's ability to better generalize on new data. The ANN is composed of two hidden layers, each containing 30 neurons, with its architecture presented in Figure 2.

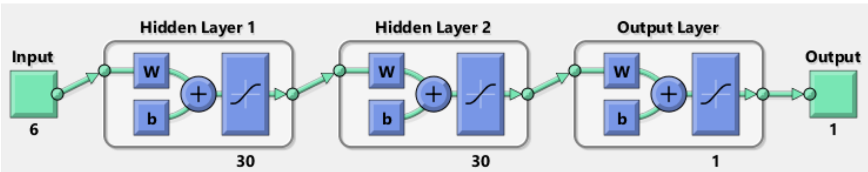
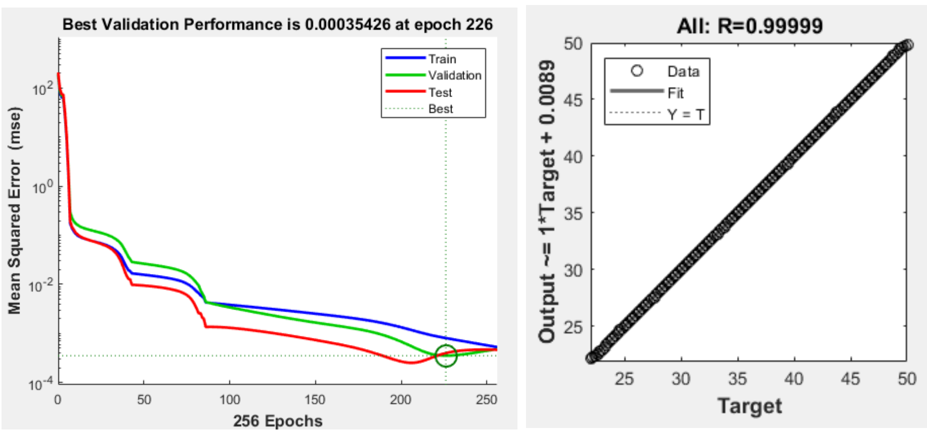


Figure 2. Network architecture



a b

Figure 3. Network performance plots

Evaluating the trained neural network's performance involves employing visualization tools such as performance curves (Figure 3a) and regression plots (Figure 3b). 70 % of the data is used for training, 15% for validation, and 15% for testing. The performance curves offer a dynamic view of the network's learning process, typically accuracy or error rate, plotted against the number of training iterations. Regression plots, on the other hand, visually compare predicted values against actual data points.

3. Evaluating the accuracy of the ANN

In the testing phase of the Artificial Neural Network (ANN), SolidWorks frequency simulations were employed to model the necessary conditions for a double-clamped beam model, as illustrated in Figure 1. The material properties were defined using plain carbon steel from the library. A fine solid mesh having 20111 nodes and 11598 total elements is applied, and the analysis is run across various thermal scenarios, simulating different temperatures affecting the beam coupled with the modal analysis, with an example illustrated in Figure 4. All defined scenarios are presented in Table 3. During each simulation, the natural frequencies for the first six bending vibration modes were recorded, starting from the reference temperature T_{ref}=22°C and continuing with other beam temperatures.

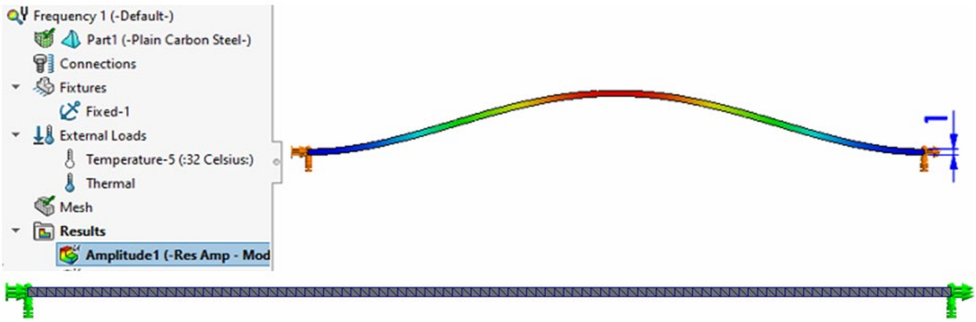


Figure 4. Frequency analysis and geometry meshing

4. Results and discussions

These frequency values served as inputs for calculating the Relative Frequency Shifts (RFSs) using Equation 8. The RFS values were utilized as testing data for the ANN. For each simulation scenario, the predicted temperatures were compared with the known temperatures obtained from SolidWorks frequency simulations. By applying several thermal conditions, the ANN's capability to accurately predict temperatures demonstrates its ability to generalize. The obtained results are presented in Table 3.

Table 3. Temperature scenarios and obtained results

Scen no.	Known temperature [°C]	Predicted temperature [°C]	Temp. difference
1	28	28.0000	0
2	22.5	22.4421	0.0579
3	23.2	23.1049	0.0951
4	23.9	23.7569	0.1431
5	33.5	33.7700	-0.270
6	42.1	41.7142	0.3858

Based on the obtained results, with errors not exceeding 0.92 %, the ANN demonstrates that it can predict the temperature with high accuracy, even when it is trained by using analytical data and tested with new data generated by simulations, thus having to deal with new RFS values that are not fitting 100% with the calculated ones, as illustrated in Figure 5 for cases 6 and 2.

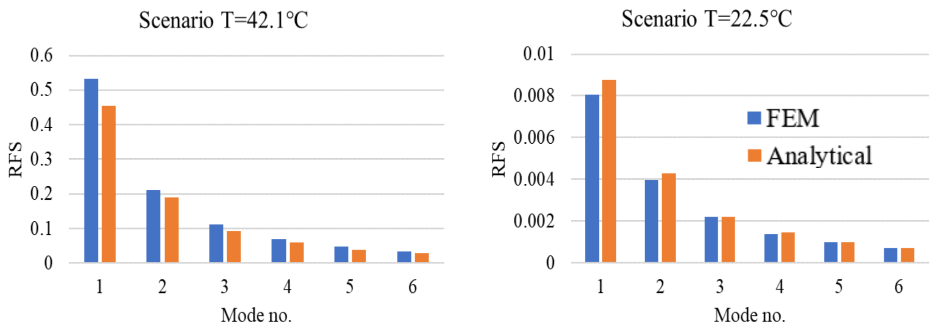


Figure 5. Comparison of calculated and FEM RFS values for scenarios 6 and 2

5. Conclusion

The current paper presents novel research for predicting the temperature by using modal parameters of structures such as the natural frequencies, coupled with intelligent learning models developed through specialized software.

An earlier developed mathematical method is used for generating the necessary training data to develop an ANN model that can predict the temperature by calculating thermal adjustment coefficients and calculating the RFS input data.

The ANN model is tested with new data, employing FEM simulations, and the results obtained illustrate a maximum deviation of 0.3858 °C, thus obtaining a temperature reading of high accuracy. Even if the accuracy does not reach that of liquid-in-glass thermometers, that can achieve a measurement uncertainty of ±0.01 °C [2], the experiment demonstrated that achieving even better temperature accuracy is feasible through the careful adjustment of hyperparameters in the Artificial Neural Network (ANN) and the utilization of a substantially larger training dataset.

The findings suggest that investing time and resources into optimizing the hyperparameters of the ANN, coupled with the acquisition of an extensive and varied dataset, can lead to significant improvements in temperature accuracy. This approach holds promise for applications where precise temperature measurements are critical, offering a pathway for enhancing the reliability and performance of temperature prediction models.

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