**Numerical Investigation of Temperature Effects on MEMS and Mitigation by Unsupervised Learning**

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**Abstract.** Temperature-induced variability poses significant challenges to the performance of micro-electro-mechanical-system (MEMS) devices, leading to changes in sensor sensitivity and zero-point drift caused by the thermal expansion or contraction of materials. These effects directly compromise the accuracy and reliability of measurements. This study numerically investigates the impacts of temperature variability on a parallel-plate cantilever configuration of a MEMS device including movable and fixed electrodes. **Accordingly, the numerical model of the MEMS device is constructed in the MATLAB environment and** temperature-dependent changes in material properties are incorporated to simulate the MEMS behavior and its thermal-induced displacements. Due to the importance of temperature effects, an unsupervised data normalizer based on an autoencoder is suggested to remove such effects and normalize the MEMS displacements. Results demonstrate that the proposed unsupervised data normalization method ensures robust correction of temperature-induced drifts of the MEMS device so that it can enhance the reliability and accuracy of MEMS outputs under fluctuating thermal conditions.

**Keywords:** Micro-Electro-Mechanical-System, Actuator, Temperature Fluctuations, Computational Mechanics, Machine Learning, Data Normalization

1. Introduction

Micro-electro-mechanical systems (MEMS) are miniaturized devices integrating mechanical and electrical components fabricated through microfabrication techniques [1,2]. These systems have rapidly evolved due to their unique combination of compactness, reliability, low power consumption, and cost-effectiveness with various applications in engineering fields. In this context, the continuous advancement and miniaturization in MEMS technology highlight their critical role in modern sensing and automation.

MEMS devices can broadly be categorized based on their operational principles and applications into several major types, including inertial sensors, resonators, and actuators [3]. In particular, inertial MEMS such as accelerometers and gyroscopes are extensively used for measuring linear accelerations and angular velocities. Resonators, including electrostatic and piezoelectric types, are essential for frequency generation and sensing applications, benefiting from their precise and stable oscillations. MEMS actuators, often employing electrostatic, thermal, or piezoelectric mechanisms, enable precise microscale movements required in positioning and micro-manipulation tasks.

Despite several advantages of miniaturization, low power consumption, and wide application range, MEMS devices are highly susceptible to environmental variations, particularly temperature fluctuations. Such variability can significantly degrade the stability and accuracy of MEMS outputs by inducing physical and material changes in the device structure [4]. Specifically, thermal expansion or contraction alters critical mechanical properties such as stiffness, damping, and Young’s modulus, while also introducing residual thermal stress [5,6]. These effects lead to zero-point drift, changes in resonant frequency, scale factor variability, and overall output instability, particularly in MEMS accelerometers, gyroscopes, and strain sensors that rely on precision mechanical displacements [4,7]. As highlighted by studies on MEMS capacitive and resonant accelerometers, these thermally induced changes can be nonlinear and device-specific, depending on material combinations, bonding adhesives, and packaging configurations [5,6]. Therefore, the understanding of thermal mechanisms and development of robust compensation strategies is crucial for maintaining the reliability and accuracy of MEMS devices across varied and harsh environments.

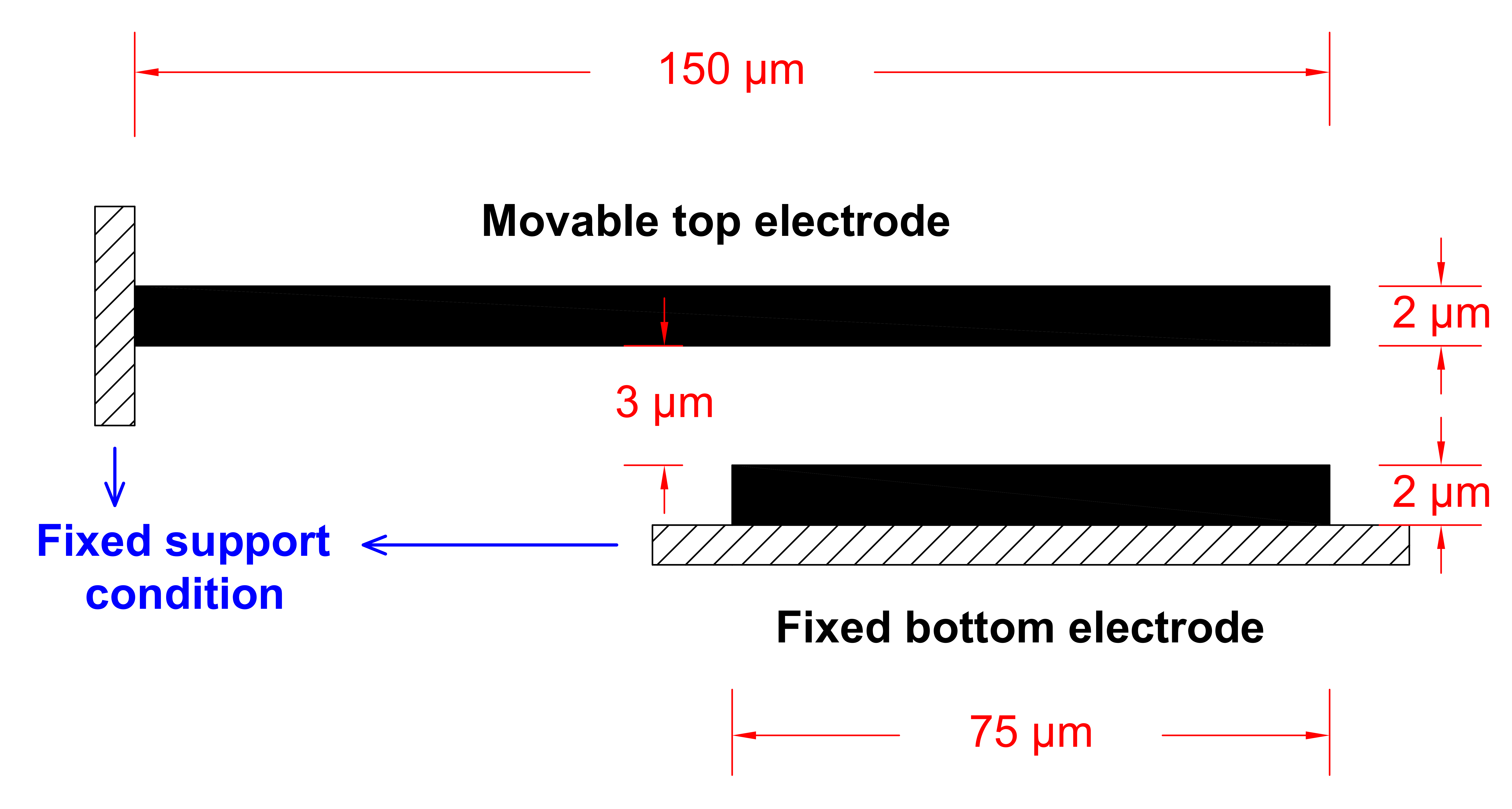
Having considered the importance and impact of temperature variability in MEMS devices, a variety of research studied have been conducted to investigate thermal effects and develop compensation approaches. Liu et al. [7] investigated the temperature sensitivity of force-balanced MEMS accelerometers and proposed a hardware-based compensation scheme to reduce scale factor and bias variations. Their study identified three main sources of thermal instability: changes in magnetic field strength, variations in coil resistance, and mechanical property fluctuations such as stiffness degradation. Guo et al. [8] presented a data-driven temperature compensation framework using deep learning techniques. Their method employed a deep long short-term memory neural network optimized by the improved sparrow search algorithm to model and compensate for temperature-induced drifts in MEMS accelerometer signals. **Lu et al. [6]** focused on MEMS resonant accelerometers, which are highly sensitive to frequency shifts under thermal stress due to the dependency of resonant frequency on Young’s modulus and axial stress. They developed a multi-layer perceptron neural network trained with a novel metaheuristic algorithm called global search artificial bee colony. Do and Seshia [5] proposed a purely structural solution for thermal compensation in MEMS capacitive strain sensors. Instead of using software or external circuits, they introduced a complement 2D interdigitated comb design that inherently cancels thermal expansion effects in two directions. Their experimental validation showed a dramatic improvement in thermal stability.

Despite developing different compensation strategies for mitigating environmental and temperature-induced effects in MEMS devices, unsupervised learning techniques within the realm of machine learning offer more adaptive and scalable alternative solutions. In contrast to traditional approaches that rely on explicit physical models or hardware calibration, unsupervised learning approaches can autonomously discover latent structures in MEMS outputs without requiring labeled samples or controlled calibration environments. Among these, reconstruction-based unsupervised models are appropriate for data normalization and compensation purposes. These models learn to replicate the dominant trends in sensor outputs influenced by environmental or operational variability. The fundamental principle of these models lies in the residual extraction, which attempt to determine the difference between the original and reconstructed data. In this context, the residual data can effectively capture and isolate deviations in MEMS outputs caused by external factors such as temperature fluctuations.

Although reconstruction-based unsupervised data normalization is a well-established approach in certain engineering applications, such as structural health monitoring [9-11], this study aims to explore another potential advantage of this methodology by applying it to compensate for temperature-induced displacement variability in MEMS devices. Accordingly, this paper numerically investigates temperature effects on MEMS and develops an autoencoder (AE)-assisted unsupervised data normalizer to eliminate thermal-induced drifts from a finite element (FE) model of a parallel-plate MEMS device consisting of movable (top) and fixed (bottom) electrodes. The FE model of the MEMS structure is constructed in the MATLAB environment. To specifically isolate and examine the intrinsic thermomechanical behavior of the MEMS device, no external electrostatic or mechanical loads are applied; instead, seasonal temperature fluctuations are simulated to assess their impact on the material properties and resulting displacements of the MEMS device. Results demonstrate that the proposed method can significantly mitigate the temperature variability in the MEMS displacements so that the AE-extracted residuals are representative of the actual MEMS outputs without the thermal effects.

1. MEMS Numerical Modeling

The MEMS model follows a parallel-plate cantilever configuration consisting of a movable top electrode (modeled as a cantilever beam) suspended above a fixed bottom electrode. The movable electrode has a length of 150 μm and a thickness of 2 μm, while the bottom electrode is 75 μm long and 2 μm thick, positioned 75 μm from the leftmost end of the top electrode. Moreover, the vertical gap between the top and bottom electrodes is 3 μm. Fig. 1 illustrates the simplified two-dimensional schematic of this MEMS device along with its main dimensions.



**Fig. 1**. Two-dimensional (2D) schematic of the MEMS along with the main dimensions

The main MEMS material is single-crystal silicon [2: Chapter 3] characterized by a Young’s modulus (*E*0) of 170 GPa and a Poisson’s ratio (*υ*) of 0.34 at the at the baseline temperature (i.e., *T*0=20°C).

* 1. Finite Element Model of the MEMS Device

The numerical model of the MEMS device is represented as a rectangular domain discretized using the finite element (FE) method in MATLAB R2023a through the Structural Mechanics module of its Partial Differential Equation (PDE) Toolbox [12]. In this context, a plane-stress model type is adopted for constructing the MEMS device. Fig. 2 illustrates the initial FE model, including labeled edge boundaries for the movable (i.e., E1, E3, E7, and E8) and fixed (i.e., E2, E4, E5, and E6) electrodes, along with the generated mesh structure. Based on the edge boundary labels, the fixed support conditions are assigned to edges E1, E2, E4, E5, and E6, while the remaining edges (i.e., E3, E7, and E8) are left free to move.

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**Fig. 2**. The FE model of the MEMS device constructed in MATLAB: (a) the edge boundary labels of the movable and fixed electrodes, (b) the generated mesh structure

Because the main purpose of this study mainly focuses on the temperature effects of the MEMS behavior and thermal-induced displacement due to material property changes, no external loads (e.g., electrostatic or mechanical loads) are applied to the FE model of the constructed MEMS device. This scenario allows us to isolate and examine the intrinsic thermos-mechanical response of the MEMS structure under seasonal temperature fluctuations. In particular, the simulation tracks the displacement variations resulting solely from temperature-dependent changes in material properties, i.e., primarily the Young’s modulus of the single-crystal silicon. In this case, the exclusion of the external forces, one can provide a clearer understanding of how temperature variations impact the MEMS structural displacements.

* 1. Temperature-Dependent Modeling

Since the FE model of the MEMS device resembles a simplified cantilever or diaphragm, thermal-induced displacement is investigated without applying external electrostatic or mechanical loads. Instead, the MEMS model is subjected to realistic thermal loading conditions reflecting seasonal temperature fluctuations over a one-year period (365 days). These thermal loads simulate daily variations in ambient temperature, allowing the assessment of their direct influence on the MEMS material properties and resulting structural displacements. Fig. 3 shows the simulated temperature fluctuations over the 365-day period applied to the MEMS model.



**Fig. 3**. Temperature fluctuations of 365 days of a year applied as thermal loads to the MEMS model

In this study, the thermal displacement behavior of the MEMS model under daily ambient temperature fluctuations is simulated using a two-dimensional (2D) plane stress formulation based on linear thermos-elasticity. The temperature-dependent mechanical response is modeled by incorporating a temperature-sensitive elastic modulus and a uniform thermal strain field into the governing equations. To realistically represent seasonal and daily thermal variability, the Young’s modulus of the MEMS device is updated at each simulation step according to the ambient temperature *T* (°C). In this regard, the Young’s modulus for the MEMS material (single-crystal silicon) is expressed as a linear function of temperature as follows:

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|  |  | (1) |

where *E*(*T*) denotes the Young’s modulus at temperature *T* (°C); *E*0 is the reference Young’s modulus at the baseline temperature *T*0; and represents the temperature coefficient of elasticity or Young’s modulus thermal coefficient (1/°C), which quantifies how much the MEMS material (i.e., silicon) expands linearly per °C [13]. This formulation reflects the reduction in stiffness as the temperature increases above the reference value, a behavior commonly observed in silicon-based MEMS materials [14].

Apart from the temperature-dependent changes in the Young’s modulus of the MEMS device, the thermal strain induced by the applied temperature field is also considered as an isotropic expansion. For a uniform temperature *T* applied across the MEMS domain, the thermal strain tensor is given by:

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|  |  | (2) |

where *ε*(*T*) is the thermal strain tensor at the temperature *T*; denotes the coefficient of the thermal expansion, which represents the fractional reduction in the Young’s modulus of the MEMS material (i.e., silicon) per °C increase in temperature [15]; and **I** stands for the identity tensor. This strain function is isotropic and added to the mechanical strain during the thermal loading. Under the assumption of the plane stress, the thermal strain vector becomes:

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|  |  | (3) |

The total strain **ε** within the structure is decomposed into mechanical and thermal parts, and the stress-strain relationship was described by the constitutive equation for thermos-elasticity:

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|  |  | (4) |

where **σ** is the stress vector and **D**(*T*) describes the elasticity matrix dependent on the current temperature. In the case of plane stress conditions, the elasticity matrix takes the form:

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|  |  | (5) |

where *υ* represents the Poisson’s ratio. This matrix ensures that the temperature-dependent stiffness is properly accounted for in the simulation. Therefore, the governing equations of equilibrium for a static, thermally loaded structure are expressed as:

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|  |  | (6) |

with the boundary conditions prescribed on the Dirichlet boundary *ΓD*, where displacements are constrained, and Neumann boundary *ΓN*, which is stress-free. Accordingly, the body force vector is set to zero, and no external electrostatic or mechanical loadings are applied to the FE model of the MEMS device. Therefore, the temperature field alone induces the internal displacement through the thermal expansion and temperature-dependent material variability. This means that the effect of temperature is imposed via a uniform temperature field​, representing the environmental temperature variation for each day.

1. Unsupervised Data Normalizer

In deep learning, the AEs are unsupervised neural networks designed to learn compressed representations of input unlabeled data by reconstructing them through a bottleneck architecture. A typical AE model consists of an encoder, which maps the input data to a lower-dimensional latent space, and a **decoder**, which reconstructs the original input data from the latent representation [16]. In this study, an AE model is employed to model and reconstruct the MEMS displacements subjected to temperature fluctuations. The key idea is that temperature-related variability forms a dominant component in the displacement data. In this case, the residuals between the original and AE-oriented reconstructed displacements serve as the normalized output of the MEMS device.

Let **y**∈ℝ*n* denotes the original MEMS displacement vector, where *n* is the number of displacement samples. A deep AE model comprises a stack of encoding and decoding layers. In this context, the encoder layers can be expressed as follows:

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where *d* represents the number of encoding layers, **W***i* and **b***i* are the weight matrix and bias vector of the *i*‑th layer, respectively, in which *i*=1,…,*d*; *fi* is the activation function; and **z**∈ℝ*m* denotes the final latent representation. The same strategy can be considered for the decoding layer in the following form:

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|  |  | (8) |

where **ŷ**∈ℝ*n* is the reconstructed version of the original displacement vector **y**; and *L* stands for the total number of hidden layers of the AE model. This model is trained by minimizing the reconstruction loss function in terms of the **mean squared error (MSE)** between the original and reconstructed displacement vectors as follows:

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Using the trained AE model on the training dataset, the residual vector, treating as the normalized MEMS displacement, is calculated as:

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|  |  | (10) |

This strategy assumes that the autoencoder learns to reconstruct the dominant temperature-related deformation patterns embedded in the displacement data. Consequently, subtracting the reconstruction from the original input yields the residuals representing temperature-invariant structural responses.

1. Results and Discussions

To simulate the thermal-induced displacements of the MEMS device, the seasonal temperature fluctuations are applied as thermal loads to the FE model of the MEMS. For this purpose, Table 1 lists the main material properties and thermal loading parameters. According to the FE model of the MEMS structure and the temperature-dependent modeling, 365 thermal loads under different temperature records are induced the MEMS device to determine its maximum displacement per temperature. Fig. 4 shows the temperature-dependent maximum displacements of the MEMS structure at the minimum and maximum recorded temperatures of –1.84 °C and 25.89 °C. From the color bars and their values in this figure, one can discern that the MEMS displacement increases by increasing the temperature. For more details, Fig. 5 indicates the variability of the maximum displacements of the MEMS model under the thermal loading.

Table 1. Material properties and thermal loading parameters for the MEMS device

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| Type | Properties | Values |
| Material | Young’s modulus (*E*0) | 170 (GPa) |
| Passion’s ration (*υ*) | 0.34 |
| Thermal loading | Young’s modulus thermal coefficient () | 5.26×10–5 (1/°C) [13] |
| Thermal expansion coefficient () | 2.65×10–6 (1/°C) [13] |
| Baseline temperature (*T*0) | 20 °C |

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**Fig. 4**. Temperature-induced maximum displacements of the FE model of the MEMS device: (a) the minimum temperature record of –1.84 °C, (b) the maximum temperature record of 25.89 °C



**Fig. 5**. Maximum displacement time series of the MEMS device under the thermal loadings using seasonal temperature changes.

Using the MEMS output (i.e., the maximum displacement time series), an AE model is developed to determine the residuals between the original and reconstructed displacement samples are the normalized outputs of the MEMS device without the temperature effects. Given that y refers to the original (temperature-dependent) MEMS displacements, it is divided into the training and testing datasets using a ratio of 70%-30%. Accordingly, the first 255 displacement points are utilized in the training data, while the remaining 110 displacement points serve as the test instances.

Table 2. Search domain and optimized values of the hyperparameters of the autoencoder

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| Hyperparameter | Search domain | Optimized values |
| Number of hidden layers | 1 – 3 | 1 |
| Number of neurons | 5 – 100 | 54 |
| Regularization values | 10-8 – 10-3 | 1.75×10-7 |

Bayesian hyperparameter optimization is considered to tune the main hyperparameters of the autoencoder including the number of hidden layers, the neurons of these layers, and *L*2 regularization value. The other options for training the autoencoder model include 1000 epochs, and logistic sigmoid and linear activation functions for the encoding and decoding procedures. Table 2 presents the search domain and the optimized values of the hyperparameters for the autoencoder-aided data normalizer. Based on the optimized hyperparameter, the AE model is trained using the training data. The test data are then fed into this model, in which one extract the normalized MEMS displacements in terms of the residuals between the original and reconstructed displacement samples.

The result of the AE-aided data normalization for the MEMS device is shown in Fig. 6. From Fig. 6(a), one can observe that the AE-oriented reconstructed displacement samples closely align with the original MEMS displacements. This means that the developed AE model could effectively capture the underlying patterns in the temperature-induced deformation data and reconstruct the displacements with high fidelity. Such alignment indicates that the AE has successfully learned the intrinsic thermos-mechanical behavior of the MEMS device, which enables it to filter out the impacts of the temperature fluctuations in the MEMS response.



**Fig. 6**. The AE-aided data normalization for the MEMS displacements: (a) the comparison between the original and reconstructed MEMS displacements, (b) the normalized displacements (AE-extracted residuals) of the MEMS device

Table 3. Performance evaluation of the proposed AE-aided data normalization

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| Phase | Metrics | |
| MSE (×10-20) | R² |
| Training | 0.4809 | 0.9893 |
| Testing | 0.6864 | 0.9016 |
| Overall | 0.5428 | 0.9898 |

To further evaluate these findings, Table 3 presents the mean squared error (MSE) and coefficient of determination (R²) metrics for the training, testing, and overall phases. In all three cases, the MSE values are negligible, while the R² values are consistently close to 1, indicating the reliable performance of the AE model without signs of underfitting or overfitting. Given this effective performance, Fig. 6(b) illustrates the normalized MEMS displacements, represented as the AE-extracted residuals. As observed, the magnitude of the normalized responses is significantly smaller than that of both the original and reconstructed displacements. This demonstrates the capability of the proposed unsupervised data normalizer to effectively eliminate temperature-induced variability in the MEMS responses.

1. Conclusions

This study aimed to investigate the temperature-induced displacement variability in MEMS devices and to develop a data-driven compensation strategy using unsupervised learning. A numerical model of a parallel-plate MEMS structure was developed in the MATLAB environment. To isolate the intrinsic thermo-mechanical behavior of the device, no external loads were applied, and only daily seasonal temperature fluctuations over a one-year period were simulated. The temperature-dependent displacements were used to evaluate the performance of an AE-assisted unsupervised data normalization method, which was adapted from the fundamental principle of a reconstruction-based strategy.

The results showed that the AE model was capable of learning and reconstructing the dominant thermal deformation patterns with high fidelity, as evidenced by low reconstruction error and high R² values in both training and testing phases. The residuals between the original and reconstructed displacement time series served as the normalized outputs, effectively filtering out the temperature-induced drifts. Compared to the original displacement data, the AE-extracted residuals exhibited significantly reduced magnitude, demonstrating its ability to isolate temperature-invariant structural responses. These findings confirm that reconstruction-based unsupervised learning offers a robust and scalable approach for thermal compensation in MEMS devices and enhances their reliability and measurement accuracy under varying environmental conditions.

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