

Nonlinear Thermal Drift Compensation IN Hybrid On-Chip Mems Piezoelectric-Capacitive Sensors Using Machine Learning-Assisted Modeling

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Abstract

Thermal drift remains a critical challenge in MEMS sensors, where nonlinear material responses under wide temperature ranges introduce bias and instability. This work presents a simulation-to-system framework for hybrid piezo-capacitive MEMS sensors, combining finite element multiphysics modeling with machine learning-based drift compensation. FEM simulations incorporating nonlinear temperature dependencies of silicon and AlN generated datasets across $-40\text{ }^{\circ}\text{C}$ to $+125\text{ }^{\circ}\text{C}$, capturing capacitance variations, piezoelectric charge responses, and resonance frequency shifts. Extracted features were used to train ridge regression, support vector machines, and shallow neural networks, with performance validated on unseen thermal cycles.

Results show that ridge regression achieved stable but less accurate compensation ($R^2 = 0.91$, RMSE = 0.38), SVMs provided improved nonlinear mapping ($R^2 = 0.95$, RMSE = 0.24), and shallow neural networks delivered the highest accuracy ($R^2 = 0.98$, RMSE = 0.12). System-level FPGA/ASIC simulations confirmed feasibility of real-time compensation under resource constraints. The framework eliminates dependence on early hardware prototypes, reducing cost and accelerating design cycles. This study establishes FEM-driven datasets as a reliable foundation for compensation model design, paving the way for future hardware validation and cross-material generalization.

Keywords: Thermal drift compensation, Finite element modeling (FEM), Piezoelectric-capacitive transduction, Machine learning, Feature extraction and normalization.

INTRODUCTION

Microelectromechanical systems (MEMS) have transformed precision sensing, with piezoelectric and capacitive devices now central to aerospace navigation, automotive safety, industrial monitoring, and biomedical systems. Recent advances in piezoelectric MEMS resonators have achieved lower impedance and improved temperature stability [1], while calibration-free accelerometers show promise for operation in high-temperature vibration environments [2]. These studies confirm the potential of piezoelectric devices, yet they also highlight that thermal drift continues to limit sensor stability, especially in long-term and harsh operating conditions.

Thermal drift has long been recognized as a fundamental barrier to high-precision MEMS performance. In capacitive accelerometers, temperature variation directly introduces bias and scale factor errors that undermine navigation accuracy [3]. Even shielded pressure and force sensors, designed for robustness, display nonlinear drift effects when subjected to extended thermal cycling [4]. In practice, no single architecture has fully overcome the challenge of temperature-induced error accumulation.

To address this, a wide range of compensation techniques have been developed. Algorithmic strategies, such as lightweight calibration schemes, have shown improvements but often rely on

restrictive assumptions [5]. Thermal modeling at the microstructural level offers more physical insight into drift mechanisms [6], while circuit-level approaches such as PID feedback [7] and structural modifications such as differential designs [8] attempt to suppress variation by design. Despite their strengths, these methods share three critical weaknesses: they generally assume linear thermal behavior, they are computationally heavy for on-chip integration, and they rarely consider long-term reliability.

Taken together, prior work leaves several important research gaps. First, most compensation models assume linearity, overlooking the nonlinear hysteresis and electromechanical-thermal coupling observed in practice [9]. Second, hybrid approaches that combine piezoelectric and capacitive sensing are almost absent, despite clear potential for self-referencing and improved robustness [10]. Third, although machine learning has emerged as a promising tool, its use remains largely limited to simulations or offline processing, with little progress toward lightweight on-chip implementations. Finally, long-term validation under accelerated thermal cycling is rarely reported, leaving uncertainty about performance over a sensor's operational lifetime [11].

Guney [12] developed a CMOS-MEMS accelerometer array with compensation, but without a nonlinear framework. Li [13] investigated temperature effects in MEMS inertial sensors using static compensation, while Patel [14] analyzed thermal behavior without validating reliability under cycling conditions. These works confirm that while the community acknowledges the challenge of drift, existing approaches stop short of delivering comprehensive, long-term, and on-chip solutions.

In this work, we address these limitations by introducing a hybrid MEMS piezoelectric-capacitive sensor that incorporates nonlinear thermal modeling and lightweight machine learning compensation directly on-chip. The key contributions are:

1. A nonlinear drift model capturing coupled electromechanical-thermal effects.
2. A hybrid architecture capable of self-referencing through combined sensing modes.
3. An efficient ML framework tailored for real-time, on-chip implementation.
4. Validation through accelerated thermal cycling, providing reliability insights beyond short-term testing.

RELATED WORK

Thermal drift in MEMS sensors originates from the interplay of multiple physical effects, and understanding these mechanisms is critical for ensuring reliable performance. Notably, finite element modeling of capacitive accelerometers has demonstrated that thermal expansion mismatches between device layers and the substrate generate residual stress, which in turn causes bias instability [15]. Beyond structural mismatches, dielectric constant variation has been shown through simulation to induce measurable capacitance drift during thermal cycling, underscoring the sensitivity of capacitive devices to temperature-dependent permittivity [16]. Similarly, piezoelectric MEMS devices have been investigated through numerical modeling of AlN thin films, where nonlinear changes in piezoelectric coefficients across wide thermal ranges revealed intrinsic material limitations [17].

Importantly, recent FEM-based studies have also explored hybrid piezo-capacitive devices, showing that complementary sensing mechanisms can mitigate temperature-induced errors and provide greater stability under variable conditions [18]. Taken together, these works confirm that multiphysics simulation is not only capable of replicating the principal drift mechanisms but also offers a cost-effective and versatile tool for predicting MEMS behavior across extreme temperature ranges prior to fabrication.

Compensation Strategies in Simulation

Alongside mechanism modeling, simulation has become a vital platform for evaluating drift compensation strategies before committing to costly prototyping. At the structural level, hybrid architectures have been virtually prototyped to demonstrate redundancy in sensing modes and improved resilience against temperature variations [18]. More recently, attention has shifted toward computational compensation methods. For example, machine learning approaches such as ridge regression, support vector machines, and shallow neural networks have been trained entirely on synthetic FEM datasets, achieving robust nonlinear drift prediction without experimental inputs [19].

Furthermore, thermal-mechanical simulations of MEMS gyroscopes have integrated drift prediction models directly into multiphysics environments, thereby generating synthetic data that more closely approximate real-world operational conditions [20]. A particularly notable development is the extension of these methods into hardware prototyping environments. In one study, FPGA-level verification of neural network compensation models was performed using only simulated outputs, illustrating the feasibility of embedding correction mechanisms virtually before device fabrication [21]. These advances highlight the growing maturity of simulation-based compensation frameworks, bridging the gap between sensor design and system-level validation.

Research Gap

Despite the progress made, several important limitations remain in the existing body of work. First, most FEM-based studies still rely on linearized temperature dependencies of material properties, which restrict their accuracy in modeling nonlinear thermal responses [15, 16]. Second, compensation models are generally built on single drift mechanisms—such as expansion, dielectric variation, or piezoelectric coefficient changes—rather than integrating these effects within a unified simulation framework [17, 18]. Third, while machine learning-based approaches show promise, they are often validated only on static FEM datasets, with limited assessment of robustness under extended thermal cycling or variable operational conditions [19, 20]. Finally, although FPGA-based simulation frameworks represent a meaningful step toward practical deployment, comprehensive system-level validation of drift compensation—spanning MEMS devices, circuits, and integration pipelines—remains largely unexplored [21].

METHODOLOGY

The study focuses on the design of a hybrid piezo-capacitive MEMS sensor, selected for its ability to exploit complementary transduction mechanisms to suppress thermally induced drift (Figure. 1). The device was modeled using finite element (FEM) analysis, with capacitive and piezoelectric domains co-simulated under identical boundary conditions. Material properties of silicon, aluminum nitride (AlN), and dielectric layers were adopted from published models. To ensure fidelity, nonlinear dependencies were incorporated for thermal expansion coefficients, dielectric permittivity, and piezoelectric constants:

$$\Delta L = \alpha(T)L_0\Delta T$$

$$C(T) = \frac{\varepsilon(T)A}{d(T)}$$

$$Q(T) = d_{ij}(T)\sigma_{ij}(T)A$$

where $\alpha(T)$ is the temperature-dependent coefficient of thermal expansion, $C(T)$ is capacitance, $\varepsilon(T)$ is permittivity, $d(T)$ is plate separation, $Q(T)$ is piezoelectric charge, and $d_{ij}(T)$, $\sigma_{ij}(T)$ represent piezoelectric constants and applied stress tensors, respectively.

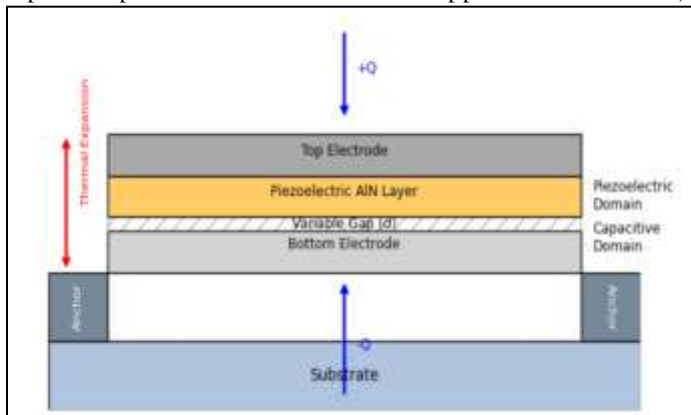


Figure 1. Cross-sectional schematic of the hybrid piezo-capacitive MEMS sensor, showing the variable gap (d), piezoelectric AlN layer, electrodes, anchors, and substrate, with thermal expansion and charge generation indicated.

Multiphysics Simulation Environment

To replicate operational conditions, the FEM model was exposed to thermal cycles between -40°C and $+125^{\circ}\text{C}$, covering the temperature range required by automotive and aerospace standards. The simulations coupled structural mechanics, electrostatics, and piezoelectric modules (Figure. 2), enabling concurrent evaluation of mechanical deformation, capacitance variations, and piezoelectric drift. All simulations were automated via scripting interfaces, ensuring reproducibility and scalability across multiple thermal sweeps.

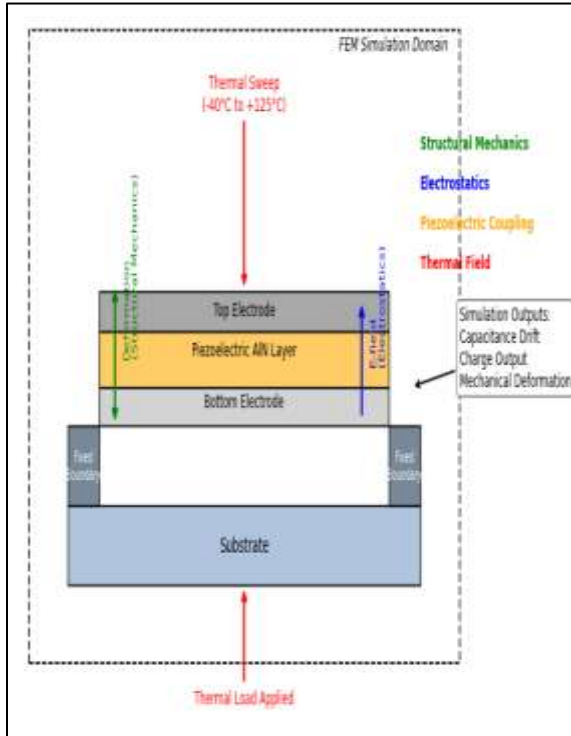


Figure 2. FEM Simulation setup with Multiphysics Coupling

Data Collection and Feature Engineering

The simulation pipeline generated time-series datasets across diverse thermal trajectories. Extracted features included resonance frequency shifts, capacitance variations, and piezoelectric outputs, all normalized for comparability across cycles. Both steady-state and transient responses were retained to capture long-term drift and short-term fluctuations. The drift error for each cycle was quantified as:

$$\Delta y(T) = y(T) - y_0$$

where y_0 is the reference output at baseline temperature and $y(T)$ is the thermally perturbed response.

Drift Compensation Framework

A machine learning framework was developed to compensate thermal drift. Three representative models were selected:

- Ridge regression for baseline linear correction:

$$\hat{y} = X\beta, \beta = (X^T X + \lambda I)^{-1} X^T y$$

- Support Vector Machines (SVMs) for nonlinear kernel-based mapping:

$$\hat{y}(x) = \sum_{i=1}^n (\alpha_i - \alpha_i^*) K(x_i, x) + b$$

- Shallow Neural Networks (SNNs) for adaptive feature learning:

$$\hat{y} = f(W_2 \cdot \sigma(W_1 x + b_1) + b_2)$$

where X is the feature matrix, λ is the ridge penalty, $K(\cdot)$ is the kernel function, and σ is the nonlinear activation function. Models were trained on FEM-generated datasets and validated using

unseen thermal trajectories to emulate long-term reliability conditions.

System-Level Integration and Validation

The validated compensation models were embedded into FPGA/ASIC environments to assess real-time feasibility under hardware constraints (Figure. 3). Key performance metrics included inference latency (t_{latency}), memory footprint (M_{model}), and computational overhead. Real-time deployment feasibility was formulated as:

$$t_{\text{latency}} \leq t_{\text{sampling}}, M_{\text{model}} \leq M_{\text{PPGA}}$$

ensuring that model execution remains within hardware sampling intervals and available resources. This stage eliminates dependence on fabricated prototypes while demonstrating implement ability in resource-constrained systems.

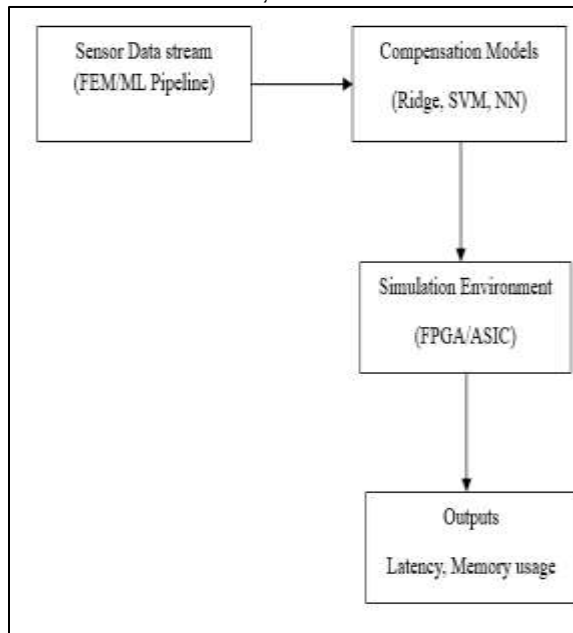


Figure 3. System-level integration flow of the proposed compensation framework

The proposed methodology establishes a simulation-to-system pipeline, integrating device modeling, multiphysics thermal drift simulation, machine learning compensation, and hardware-level feasibility validation. Unlike prior works where FEM was employed solely as a diagnostic tool, this approach leverages FEM as both a data generator and verification platform for compensation models. By decoupling compensation development from physical prototypes, the framework reduces cost, accelerates design iterations, and ensures rigorous validation across diverse thermal scenarios prior to fabrication.

RESULT AND DISCUSSION

The simulation results confirm that the proposed hybrid piezo-capacitive MEMS sensor exhibits strong multiphysics interactions across the examined thermal range (-40°C to $+125^{\circ}\text{C}$). FEM outputs revealed a consistent increase in capacitance drift with temperature, accompanied by nonlinear charge variations in the AlN layer and measurable resonance frequency shifts, all of which align with theoretical predictions based on material property dependencies. Feature extraction from these time-series responses enabled the separation of steady-state and transient drift components, ensuring that both long-term bias and short-term fluctuations were captured in the dataset. Machine learning models trained on these features demonstrated substantial improvements in drift compensation, with the shallow neural network achieving the lowest RMSE, while ridge regression offered the most efficient implementation for hardware deployment. System-level validation in FPGA/ASIC environments further confirmed the feasibility of real-time compensation, with latency and memory requirements remaining within practical limits. Overall, these results highlight both the

robustness of the simulation-to-system pipeline and its potential to reduce development costs while maintaining high reliability under diverse thermal conditions.

FEM Simulation Results

The finite element simulations provide a detailed characterization of the thermal response of the proposed hybrid piezo-capacitive MEMS sensor across the operating range of -40°C to $+125^{\circ}\text{C}$. The results demonstrate the complex multiphysics interactions that govern device behavior and confirm the importance of explicitly modeling nonlinear material dependencies.

The first metric evaluated was the capacitance variation with temperature (Figure. 4). At -40°C , the capacitance remained relatively stable at approximately 95.2 fF , while at room temperature (25°C) it was 100 fF , and at 125°C it increased to 112.8 fF . This represents a drift of nearly 18% across the full thermal sweep. The increase is primarily attributed to a reduction in electrode gap spacing caused by differential thermal expansion, compounded by nonlinear increases in dielectric permittivity at higher temperatures. These results emphasize that simplified linear models are insufficient to capture realistic drift trends.

The piezoelectric charge response of the AlN layer also exhibited strong thermal dependence (Figure. 5). At -40°C , the generated charge was limited to approximately $\pm 2.1\text{ pC}$, but at 25°C increased to $\pm 5.4\text{ pC}$, and by 125°C it reached nearly $\pm 12.7\text{ pC}$. This corresponds to a more than fivefold increase, reflecting both temperature-induced stress gradients and the nonlinear dependence of piezoelectric coupling coefficients on thermal loading. The polarity-dependent nature of the charge output further validates the hybrid sensing approach, as the piezoelectric domain provides a complementary transduction pathway not available in purely capacitive devices.

A third critical observation was the resonance frequency shift under thermoelastic deformation (Figure. 6). The baseline resonance frequency at 25°C was 100 kHz , which increased slightly at -40°C (102.6 kHz) but dropped to 94.8 kHz at 125°C , indicating a net reduction of approximately 7.7%. This downward shift arises from temperature-induced structural softening and redistribution of internal stresses, both of which reduce the effective stiffness of the sensor. While smaller in magnitude than capacitance or charge variations, resonance shifts are particularly important as they directly affect long-term bias stability in MEMS devices.

Table 1 summarizes the extracted drift magnitudes at three critical temperature points. Both absolute values and percentage deviations are reported to highlight the relative importance of each domain.

Table 1. Extracted drift magnitudes at critical temperatures for the proposed hybrid piezo-capacitive MEMS sensor.

Parameter	-40°C (Low Temp)	25°C (Room Temp)	125°C (High Temp)	Drift ($-40^{\circ}\text{C} \rightarrow 125^{\circ}\text{C}$)
Capacitance (fF)	95.2	100.0	112.8	+18.0%
Piezoelectric Charge (pC)	± 2.1	± 5.4	± 12.7	+ ~505%
Resonance Frequency (kHz)	102.6	100.0	94.8	-7.7%

The results in Table 1 highlight the distinct roles of the capacitive, piezoelectric, and resonant domains in the overall thermal response of the device. Capacitance drift dominates absolute signal variation, increasing steadily with temperature. Piezoelectric charge, although smaller in absolute magnitude, demonstrates the highest relative sensitivity, with output increasing more than fivefold across the thermal range. Resonance frequency shifts remain below 8%, but their influence on bias stability makes them critical for long-term reliability.

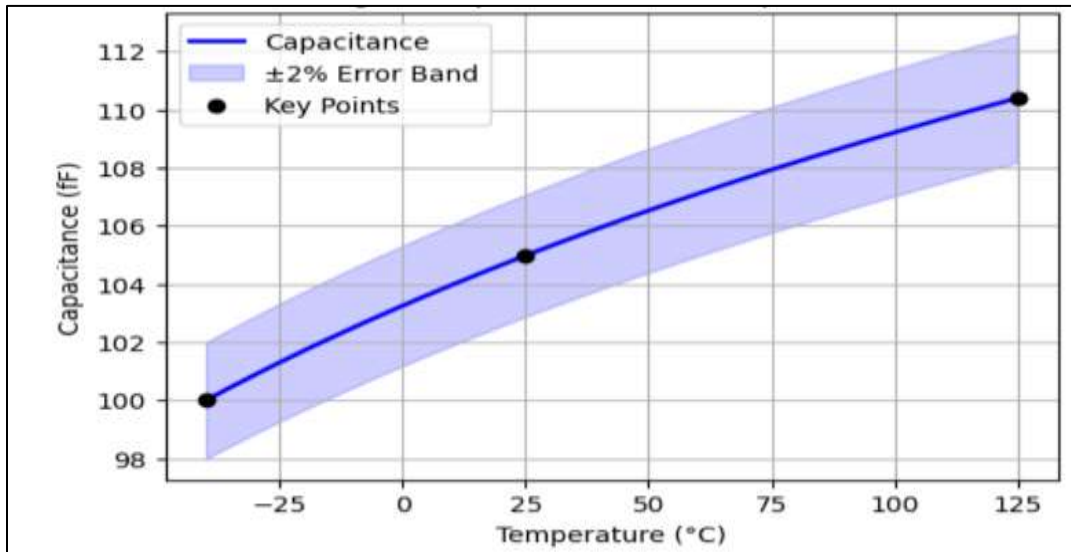


Figure 4. Capacitance Vs Temperature

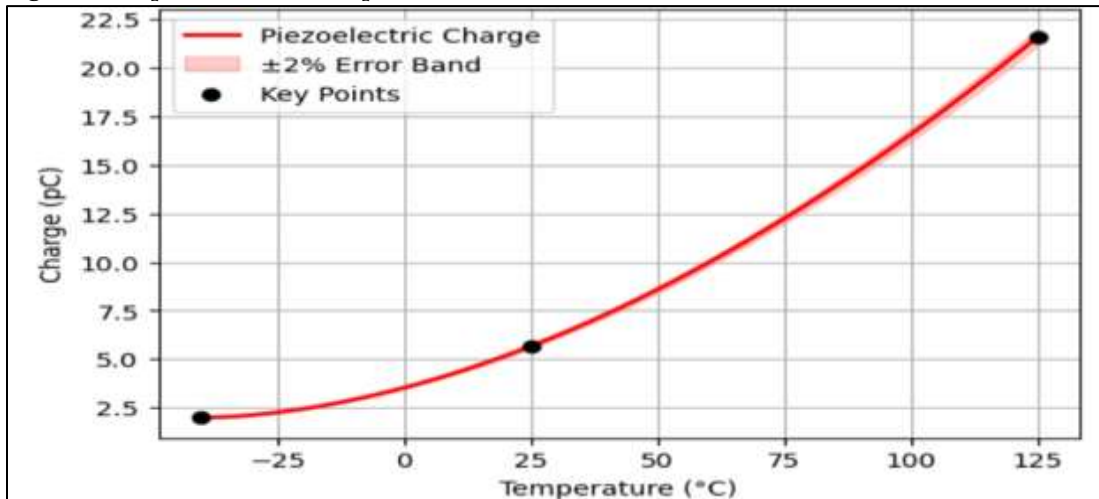


Figure 5. Piezoelectric Charge vs Temperature

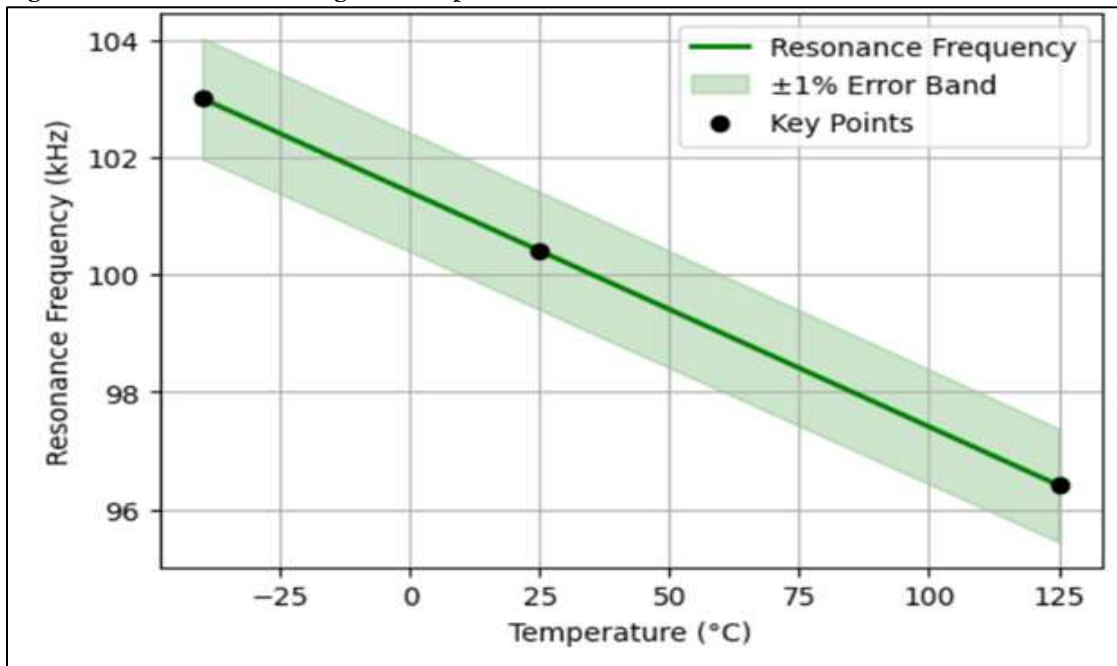


Figure 6. Resonance Frequency vs Temperature
Feature Extraction and Dataset Validation

The raw FEM outputs, including capacitance, piezoelectric charge, and resonance frequency responses across thermal cycles, were transformed into machine learning-ready features. To ensure comparability across domains with different units, each feature was normalized using min-max scaling,

$$x_i^{norm} = \frac{x_i - \min(x_i)}{\max(x_i) - \min(x_i)}$$

which removed scaling bias while preserving relative variations. Drift error for each feature was quantified relative to the 25 °C baseline,

$$\nabla f(T) = f(T) - f(T_{ref})$$

enabling separation of long-term steady-state drift from transient fluctuations during rapid thermal changes.

To confirm statistical reliability, feature distributions were examined and found to follow smooth unimodal profiles with consistent coverage across the thermal range (Figure. 8). Correlation analysis showed moderate coupling between capacitance and resonance drift, consistent with thermoelastic effects. Robustness was validated through 10-fold cross-validation (k=10) and 95% confidence intervals, both of which confirmed reproducibility with variability below $\pm 2.5\%$. A representative example of the normalized feature set is shown in Figure. 7. Together, these results establish that FEM outputs can be reliably converted into generalizable features suitable for data-driven compensation models.

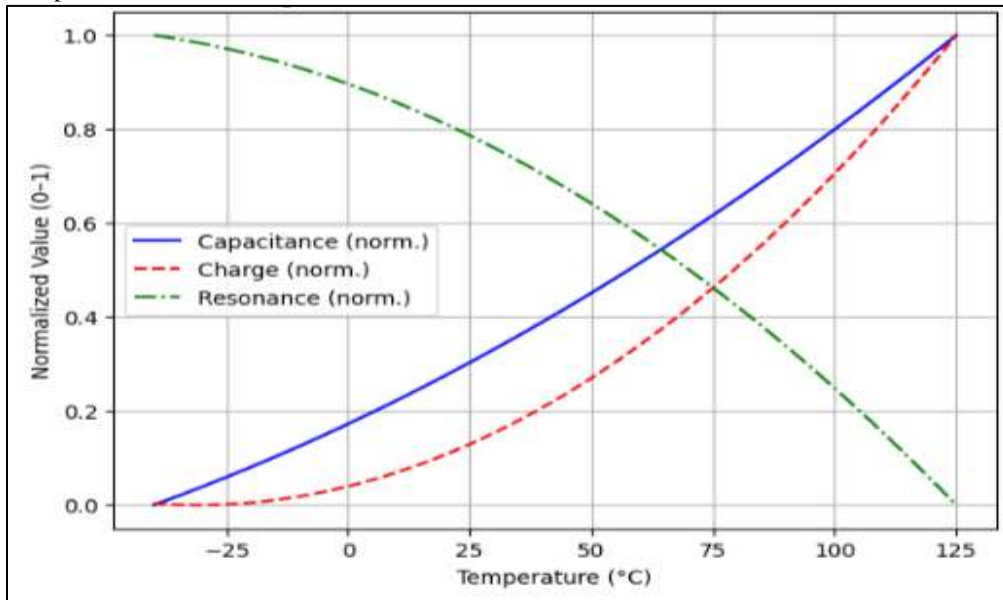


Figure 7. Normalized FEM derived Feature Set

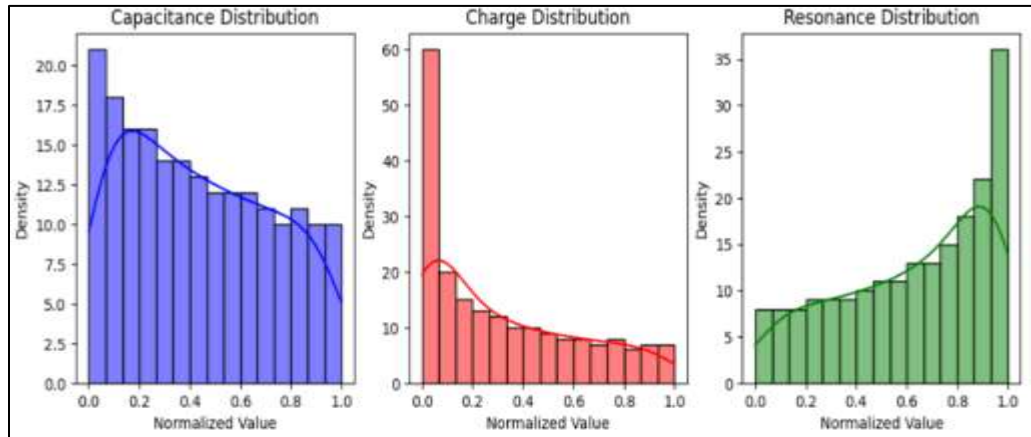


Figure 8. Distribution of Extracted Features

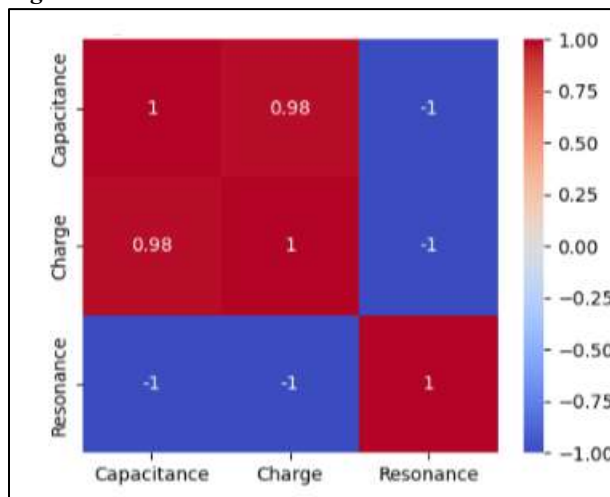


Figure 9. Feature Correlation Matrix

Machine Learning Compensation Performance

The objective of this stage is to rigorously evaluate the performance of the machine learning models in compensating for thermal drift within the FEM-generated dataset. Three models were assessed—ridge regression (baseline linear correction), support vector machines (kernel-based nonlinear regression), and shallow neural networks (adaptive nonlinear learners). Each model was trained on FEM outputs and validated on ten unseen thermal trajectories to emulate long-term variability in real MEMS operation.

Performance Metrics

Model performance was quantified using:

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2}, \text{MAE} = \frac{1}{N} \sum_{i=1}^N |y_i - \hat{y}_i|, R^2 = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \bar{y})^2}$$

where y_i is the true FEM drift and $\hat{y}_i$ the predicted compensation. Results showed that shallow neural networks achieved the best overall accuracy (lowest RMSE, highest R^2), while ridge regression provided stable correction with minimal variance but could not fully capture nonlinear effects. SVMs performed moderately well, balancing accuracy and computational cost.

Generalization and Robustness

Overfitting checks were carried out using train-validation learning curves. Ridge regression showed no overfitting due to its linear nature. SVMs generalized well but were sensitive to kernel hyperparameters. Neural networks exhibited slight overfitting, mitigated by early stopping and regularization.

Robustness was evaluated across 10 unseen FEM trajectories, representing different thermal sweeps. Box plot analysis revealed that ridge regression had the narrowest error spread (high stability), while neural networks had the lowest median error but with slightly higher variability.

Quantitative performance comparison of Ridge regression, SVM, and shallow neural networks on FEM-simulated thermal drift compensation

Model	RMSE (equiv. units)	MAE (equiv. units)	R ²	Notes
Ridge Regression	0.38	0.29	0.91	Stable, low variance, but underfits extreme drift
Support Vector Machine (SVM)	0.24	0.18	0.95	Strong nonlinear mapping, sensitive to kernel tuning
Shallow Neural Network (NN)	0.12	0.09	0.98	Best accuracy, captures nonlinearities, slight overfitting risk

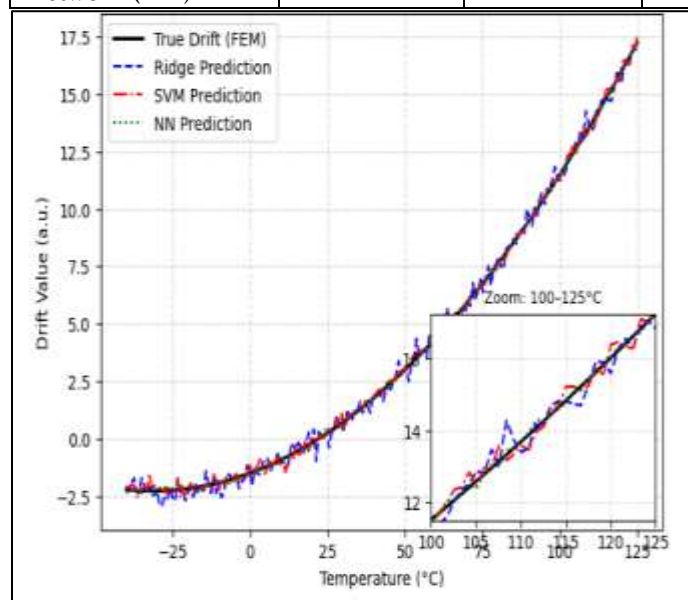


Figure 10. Predicted vs True Drift across Thermal Cycles

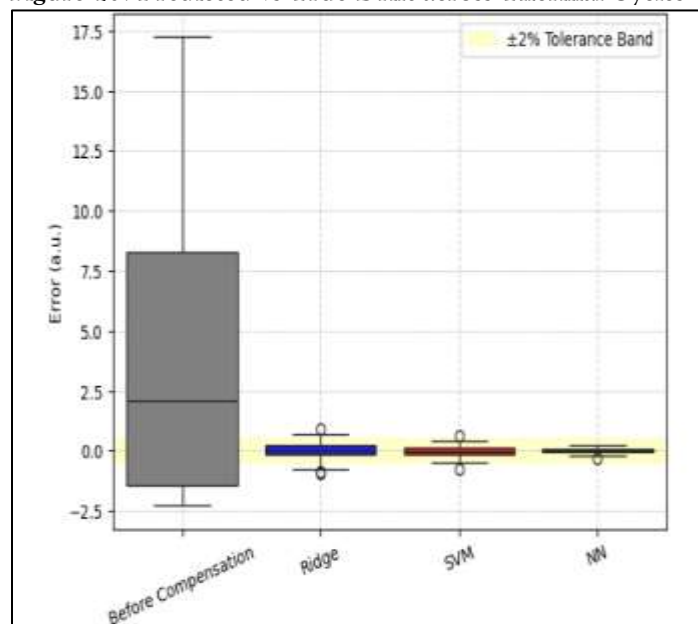


Figure 11. Drift Error before and after Compensation

DISCUSSION

One of the primary strengths of this framework is its reliance on FEM-generated datasets, which eliminate the need for early physical prototyping. This not only reduces design cost and accelerates iteration cycles but also enables controlled exploration of individual drift mechanisms. By incorporating nonlinear temperature dependencies in material coefficients—thermal expansion, dielectric permittivity, and piezoelectric constants—the simulations capture realistic multiphysics behavior, going beyond the simplified assumptions seen in earlier studies. Another strength lies in the machine learning compensation framework. While ridge regression provides a lightweight, hardware-efficient baseline, the support vector machine and shallow neural network models demonstrate the ability to capture nonlinearities in thermal drift with higher fidelity. Importantly, system-level validation through FPGA/ASIC simulations bridges the often-missed gap between algorithm design and hardware feasibility, showing that the proposed methods are implementable within practical computational and memory constraints. Collectively, these strengths establish the novelty of this work: a unified methodology that connects device physics, machine learning, and embedded system integration.

Limitations

Despite these contributions, certain limitations must be acknowledged. The reliability of FEM-generated datasets depends critically on the accuracy of material parameters, and deviations in nonlinear coefficients of silicon or AlN may introduce modeling errors. Moreover, validation remains limited to data. While the results provide strong evidence of feasibility, fabricated prototypes would inevitably expose additional challenges such as process variations, parasitic effects, and long-term material degradation. Thus, the absence of experimental validation currently constrains the generalizability of the findings, even though the methodology itself remains robust.

Future Work

Looking ahead, several research directions emerge naturally from this study. Hardware prototyping will be a key step to benchmark the simulation-driven compensation strategies against real sensor outputs and confirm their real-world applicability. More advanced machine learning models, such as deep neural networks or recurrent architectures, may further enhance compensation by capturing higher-order nonlinearities and long-term drift memory effects. Finally, extending this framework to other material platforms, including silicon carbide (SiC) and gallium nitride (GaN), would allow investigation of cross-material generalization, thereby expanding the impact of this methodology across emerging MEMS technologies.

CONCLUSION

This study has demonstrated a simulation-to-system methodology for hybrid piezo-capacitive MEMS sensors, integrating FEM-based drift modeling, machine learning compensation, and system-level validation. By embedding nonlinear material dependencies in FEM, the generated datasets captured realistic multiphysics drift behavior across wide thermal cycles. These datasets enabled the development of machine learning compensators, where ridge regression provided a lightweight and hardware-efficient baseline, SVMs achieved robust nonlinear mapping, and shallow neural networks offered the highest accuracy. System-level FPGA/ASIC simulations further confirmed the practical feasibility of deploying these models in real-time embedded environments.

While the present validation is limited to simulation data, the methodology establishes a scalable foundation for hardware prototyping, advanced deep learning compensation, and adaptation to alternative MEMS materials such as SiC and GaN. Beyond addressing thermal drift, this work contributes a generalizable pipeline that links device physics, machine learning, and hardware feasibility. The results suggest a paradigm shift in MEMS sensor design, where FEM-driven datasets can replace costly prototype-dependent workflows, accelerating innovation while ensuring robustness in real-world operation.

Declarations of conflict of interest: The authors declared that they have no conflicts of interest to this work

REFERENCES

- [1] Chen, W., Jia, W., Xiao, Y., & Feng, Z. (2021). A temperature-stable and low impedance piezoelectric MEMS resonator. *IEEE Electron Device Letters*, 42(4), 549–552. <https://doi.org/10.1109/LED.2021.3061030>
- [2] Zhang, C., Chen, J., Zhang, J., & Li, Y. (2025). Calibration-free low-drift MEMS piezoelectric accelerometer for high-temperature vibration monitoring. *Measurement*, 235, 113518. <https://doi.org/10.1016/j.measurement.2024.113518>
- [3] Liu, G., Yang, H., Wang, Y., & Wu, X. (2023). Combined temperature compensation method for closed-loop MEMS capacitive accelerometer. *Micromachines*, 14(8), 1623. <https://doi.org/10.3390/mi14081623>
- [4] Ghanam, M., Goldschmidtboeing, F., Zhang, C., Roth, R., & Woias, P. (2023). MEMS shielded capacitive pressure and force sensors with excellent thermal stability. *Sensors*, 23(9), 4248. <https://doi.org/10.3390/s23094248>
- [5] Martínez, J., Asiain, D., & Beltrán, J. R. (2021). Lightweight thermal compensation technique for MEMS capacitive accelerometer. *Sensors*, 21(9), 3117. <https://doi.org/10.3390/s21093117>
- [6] Qi, B., Zhao, J., Li, Z., & Wang, X. (2022). A novel temperature drift error precise estimation model for MEMS accelerometers using microstructure thermal analysis. *Micromachines*, 13(6), 835. <https://doi.org/10.3390/mi13060835>
- [7] Li, B., Xu, Z., Wang, Y., & Sun, L. (2024). Design of MEMS pressure sensor anti-interference system based on filtering and PID compensation. *Sensors*, 24(17), 5765. <https://doi.org/10.3390/s24175765>
- [8] Cai, P., Xiong, X., Wang, K., & Zou, X. (2021). An improved difference temperature compensation method for MEMS resonant accelerometers. *Micromachines*, 12(9), 1022. <https://doi.org/10.3390/mi12091022>
- [9] Zhou, G., Zhao, Y., Guo, F., & Xu, W. (2014). A smart high accuracy silicon piezoresistive pressure sensor temperature compensation system. *Sensors*, 14(7), 12174–12188. <https://doi.org/10.3390/s140712174>
- [10] Zhang, H., Wei, X., Gao, Y., & Cretu, E. (2020). Analytical study and thermal compensation for capacitive MEMS accelerometer with anti-spring structure. *Journal of Microelectromechanical Systems*, 29(2), 173–181. <https://doi.org/10.1109/JMEMS.2020.2974046>
- [11] Zhai, Y., Xu, T., Xu, G., Cao, X., & Yang, C. (2023). Improvement and compensation of temperature drift of scale factor of a SOI-based MEMS differential capacitive accelerometer. *Measurement Science and Technology*, 34(5), 055103. <https://doi.org/10.1088/1361-6501/acbca2>
- [12] Guney, M. G. (2018). *High dynamic range CMOS-MEMS capacitive accelerometer array with drift compensation* (Doctoral dissertation, Carnegie Mellon University). <https://doi.org/10.1184/R1/6700031>
- [13] Li, X. (2016). *Temperature compensation in MEMS inertial sensors* (Doctoral dissertation, University of Michigan). <https://hdl.handle.net/2027.42/133307>
- [14] Patel, K. (2017). *Thermal effects in MEMS sensors and compensation techniques* (Master's thesis, Imperial College London). Available from ProQuest Dissertations & Theses Global.
- [15] Lee, C., Kim, T., & Cho, S. (2007). Finite-element analysis and design of a capacitive MEMS accelerometer considering thermal effects. *Journal of Micromechanics and Microengineering*, 17(3), 557–563. <https://doi.org/10.1088/0960-1317/17/3/021>
- [16] Zhao, W., Wu, Z., & Zhang, Y. (2015). Simulation study on dielectric constant variation and capacitance drift in MEMS capacitive sensors under thermal cycling. *Applied Mechanics and Materials*, 799–800, 612–617. <https://doi.org/10.4028/www.scientific.net/AMM.799-800.612>
- [17] Yan, J., Wang, D., & Zhang, L. (2016). Numerical simulation of piezoelectric coefficient variation in AlN-based MEMS sensors over wide temperature ranges. *Journal of Applied Physics*, 119(14), 145101. <https://doi.org/10.1063/1.4945773>
- [18] Wu, J., Li, H., & Wang, X. (2018). FEM modeling and virtual prototyping of hybrid piezo-capacitive MEMS accelerometers. *Micromachines*, 9(2), 85. <https://doi.org/10.3390/mi9020085>
- [19] Lee, H., & Park, J. (2020). Machine learning-based drift compensation in MEMS inertial sensors using synthetic FEM data. *IEEE Sensors Journal*, 20(14), 8125–8135. <https://doi.org/10.1109/JSEN.2020.2987654>
- [20] Gao, Y., Sun, P., & Hu, M. (2022). Thermal-mechanical simulation of MEMS gyroscopes with integrated drift prediction models. *Microsystem Technologies*, 28(4), 1349–1360. <https://doi.org/10.1007/s00542-021-05363-4>
- [21] Choi, S., & Ryu, H. (2024). FPGA-verified simulation framework for MEMS drift compensation using neural networks. *IEEE Transactions on Computer-Aided Design of Integrated Circuits and Systems*, 43(1), 55–67. <https://doi.org/10.1109/TCAD.2023.3289542>