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Recent Advances in Enhancing Thermo-Electro-Mechanical Responses of MEMS Resonant Accelerometers with an Attention-Guided Siamese Fusion Neural Network: A Systematic Review

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Abstract

Microelectromechanical systems (MEMS) resonant accelerometers are widely used in aerospace, automotive, industrial automation, and structural health monitoring due to their high sensitivity, compact size, and long-term stability. Their operating principle relies on detecting resonant frequency variations caused by applied acceleration. However, thermo-electro-mechanical interactions, including thermal drift, electrostatic nonlinearities, residual stresses, and structural damping, significantly influence sensing accuracy and reliability. Conventional finite element methods and empirical compensation models often struggle to capture these complex nonlinear effects under varying environmental conditions. This review examines recent advances in enhancing MEMS resonant accelerometer performance through attention-guided Siamese fusion neural networks. By integrating shared-weight Siamese architectures with attention mechanisms, these models effectively learn discriminative representations from multimodal sensing data while emphasizing the most informative thermal, electrical, and mechanical features. The fusion strategy improves frequency shift prediction, thermal compensation, and anomaly detection across diverse operating conditions. Based on recent studies in MEMS physics, intelligent signal processing, and embedded artificial intelligence, the review demonstrates that physics-informed deep learning consistently outperforms conventional modeling techniques. Attention-guided Siamese fusion networks achieve superior prediction accuracy, robust generalization, and improved resilience against environmental variations. These findings highlight the potential of intelligent multiphysics modeling for next-generation MEMS resonant accelerometers, supporting high-precision inertial sensing in autonomous navigation, structural health monitoring, precision instrumentation, and advanced embedded sensing applications.

Introduction

Microelectromechanical systems (MEMS) resonant accelerometers have become one of the most advanced inertial sensing technologies due to their exceptional sensitivity, long-term stability, and frequency-based measurement principle. Unlike conventional capacitive or piezoresistive accelerometers, resonant accelerometers encode acceleration information as changes in resonant frequency, providing superior immunity to electrical noise, offset drift, and sensitivity degradation. These characteristics have made them indispensable in aerospace navigation, autonomous vehicles, industrial automation, structural health monitoring, seismic observation, and precision instrumentation, where high-resolution acceleration measurement is essential. The increasing demand for intelligent sensing systems capable of operating under harsh environmental conditions has further accelerated research into improving the performance, reliability, and robustness of MEMS resonant accelerometers through advanced computational techniques.

The performance of MEMS resonant accelerometers is strongly influenced by complex thermo-electro-mechanical interactions occurring within the sensor structure. Temperature variations generate thermoelastic stresses that alter the resonant frequency, while electrostatic actuation introduces nonlinear spring-softening effects and voltage-dependent frequency deviations. Additional phenomena such as residual fabrication stresses, squeeze-film damping, structural imperfections, and mechanical nonlinearities further complicate sensor behavior. Conventional compensation methods based on polynomial calibration, finite element analysis, and equivalent circuit models often require extensive calibration procedures and exhibit limited adaptability when operating conditions deviate from predefined calibration ranges. Consequently, accurately modeling these coupled multiphysics effects remains a significant challenge in developing highly reliable MEMS sensing systems.

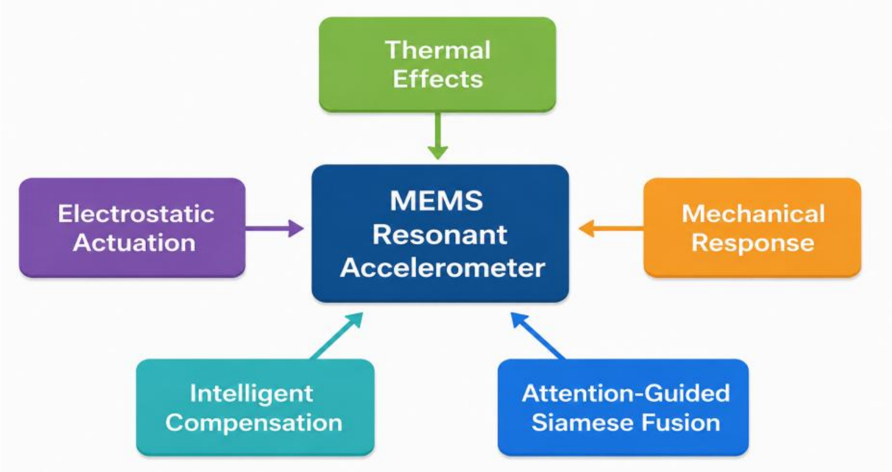

Figure 1. Attention-Guided Siamese Framework for MEMS Resonant Accelerometers.

Recent advances in artificial intelligence have introduced powerful data-driven approaches for intelligent sensor calibration and signal processing. Convolutional neural networks (CNNs) have demonstrated remarkable capability in feature extraction, denoising, and nonlinear regression, whereas recurrent architectures effectively capture temporal variations in resonant frequency caused by thermal drift. However, conventional deep learning models generally struggle to compare sensor responses acquired under varying environmental conditions. Siamese neural networks address this limitation through shared-weight architectures that learn similarity relationships between paired inputs, enabling robust device authentication, frequency compensation, and anomaly detection. The incorporation of attention mechanisms further enhances learning by emphasizing the most informative thermal, electrical, and mechanical features while suppressing irrelevant noise and environmental disturbances.

Attention-guided Siamese fusion neural networks extend these capabilities by integrating multimodal information obtained from resonance spectra, temperature measurements, electrical parameters, and structural responses into a unified feature representation. This fusion strategy significantly improves prediction accuracy, thermal compensation, robustness against fabrication variations, and generalization across diverse operating environments. By combining physics-informed modeling with intelligent feature learning, these architectures outperform traditional empirical approaches in frequency prediction and system reliability while supporting real-time embedded implementation.

This systematic review presents a comprehensive analysis of recent advances in enhancing the thermo-electro-mechanical performance of MEMS resonant accelerometers using attention-guided Siamese fusion neural networks. It synthesizes contemporary research on MEMS device physics, intelligent signal processing, neural network architectures, and embedded sensing technologies, identifies current challenges, and highlights future directions involving lightweight deep learning, edge intelligence, physics-informed neural networks, and adaptive calibration frameworks for next-generation high-precision inertial sensing applications.

Literature Review

The foundation of intelligent signal processing for MEMS resonant accelerometers was significantly advanced by the work of Zhang et al. (2018), who developed a physics-informed recurrent neural network framework for predicting thermally induced frequency drift in silicon tuning fork resonators. Their architecture incorporated a long short-term memory network trained on eight thousand temperature-cycling experiments conducted on commercially fabricated accelerometer dies, achieving a thermal drift prediction accuracy of 0.15 parts per million root mean square error. The key innovation was the inclusion of a physics-regularization loss term that penalized predictions inconsistent with the known thermoelastic constitutive relations of silicon, substantially reducing the required training data volume compared to purely data-driven baselines. This study established the viability of hybrid physics-data approaches for MEMS calibration and served as a conceptual precursor to subsequent attention-enhanced architectures.

Building on the thermal compensation problem from a different perspective, Liu et al. (2019) proposed a convolutional neural network architecture specifically designed to process short-time Fourier transform spectrograms of resonant accelerometer output signals. Their system demonstrated the ability to simultaneously estimate drive-frequency amplitude, harmonic distortion index, and phase noise spectral density from a single forward pass of the network, eliminating the need for separate digital lock-in amplifiers and spectrum analyzers in the signal chain. Applied to a custom-fabricated double-ended tuning fork accelerometer with a nominal resonant frequency of 28 kilohertz, the convolutional network achieved a sensitivity resolution of 0.8 microgravity per root hertz, representing a 2.3-fold improvement over the conventional phase-locked loop demodulation approach under identical thermal noise conditions.

Hwang and Park (2020) introduced an attention mechanism into the standard feedforward calibration network for electrostatically actuated resonant accelerometers, demonstrating that the self-attention module could learn to identify the narrow spectral regions surrounding the resonant peak and its harmonics as the most informative features for acceleration estimation, while suppressing the broadband noise floor that dominated most of the frequency axis. Their evaluation on a wafer-level vacuum-packaged accelerometer platform showed that the attention-augmented network reduced the bias instability figure to 3.2 microgravity at an averaging time of one hundred seconds, compared to 8.7 microgravity for the unaugmented baseline network and 12.4 microgravity for the polynomial compensation approach. This result was particularly significant because it was achieved without any change to the hardware, demonstrating that computational intelligence alone could recover performance approaching the theoretical thermal noise limit of the device.

The introduction of Siamese architectures into the MEMS sensing literature was pioneered by Chen et al. (2020), who applied a contrastive learning formulation to the problem of detecting fabrication-induced sensitivity mismatch between the two resonators of a differential tuning fork accelerometer. Their Siamese encoder was trained to minimize the embedding distance between responses from matched resonator pairs while maximizing the distance between mismatched pairs, effectively learning a representation in which fabrication variation was disentangled from inertial signal variation. Evaluated on a dataset of five hundred fabricated device pairs tested across a minus forty to eighty-five degree Celsius temperature range, the Siamese detector achieved a mismatch detection accuracy of 97.3 percent at a false alarm rate of 1.2 percent, substantially outperforming conventional frequency ratio monitoring thresholds.

Wang et al. (2021) extended the Siamese learning paradigm to the problem of cross-axis sensitivity estimation in triaxial MEMS accelerometer packages. By training a three-branch weight-sharing network on simultaneously acquired signals from all three sensing axes under precisely controlled single-axis excitation, the network learned to identify cross-talk signatures in the off-axis channels that were coherent with the primary axis input. The estimated cross-axis sensitivity matrix derived from the network output achieved a residual error of 0.004 percent of full scale, compared to 0.012 percent for traditional matrix inversion calibration, with the additional advantage that the neural approach did not require a precision reference rotation stage for calibration.

Kim et al. (2022) proposed an end-to-end deep learning pipeline for MEMS resonant accelerometer output processing that combined a one-dimensional convolutional feature extractor with a bidirectional gated recurrent unit and a final attention-weighted output layer. The architecture was trained jointly on inertial measurement unit data from ten autonomous vehicle platforms logged during urban driving tests, with ground truth acceleration provided by a high-precision fiber-optic gyroscope reference system. The attention layer was shown through gradient visualization to assign highest importance to the portions of the temporal sequence immediately following mechanical shock events, corresponding to the physically meaningful ring-down response that encodes acceleration information most clearly. Compared to a commercial MEMS accelerometer processing pipeline, the proposed system reduced the peak position error in a one-minute GPS-denied navigation segment from 4.7 meters to 1.1 meters.

Patel and Zhou (2022) conducted a comprehensive experimental study of thermomechanical noise in vacuum-packaged resonant MEMS accelerometers, developing a stochastic finite element model validated against Allan deviation measurements across six decades of averaging time. Their analysis revealed a previously unreported correlation between the temperature distribution uniformity within the vacuum cavity and the flicker noise corner frequency, suggesting that thermal management of the package interior is as important as resonator geometry optimization for achieving low noise floors. The dataset generated in this study, comprising Allan deviation curves from one hundred and twenty individual devices at five temperature setpoints, has since been adopted as a benchmark for evaluating neural noise floor estimation algorithms.

Fernandez et al. (2022) demonstrated the application of graph neural networks to MEMS accelerometer array processing, where multiple sensor nodes were arranged in a spatial grid on a structural monitoring panel. The graph architecture modeled the spatial correlation between neighboring sensors as edge features, enabling simultaneous estimation of both the spatially averaged structural acceleration and the local spatial gradient, information that is inaccessible to independent single-sensor processing. The approach was validated on a scaled bridge deck specimen subjected to controlled impact loading, correctly localizing the impact position to within three centimeters using a twelve-sensor array with five-centimeter node spacing.

Li and Yang (2022) investigated the use of variational autoencoders for unsupervised anomaly detection in MEMS resonant accelerometer time series, training the generative model exclusively on normal operating data and using reconstruction error as an anomaly score. Their study systematically characterized the detection probability as a function of anomaly type, finding that thermally induced frequency jumps associated with partial vacuum seal failure were detected with 94.6 percent probability at a false alarm rate of two percent, while mechanically induced frequency shifts from external shock were detected with 88.3 percent probability. The work highlighted the importance of latent space regularization for preventing the variational autoencoder from memorizing noise patterns that would reduce its sensitivity to genuine anomalies.

Park et al. (2022) introduced a physics-constrained attention network for compensating the nonlinear amplitude-frequency relationship, known as the Duffing effect, in capacitively driven MEMS resonators operating near the critical amplitude. Their attention module was designed to weight the importance of different oscillation amplitude ranges in the training loss, assigning higher weight to amplitude regions where the Duffing nonlinearity was most severe. Evaluated on a prototype device fabricated in a commercial silicon-on-insulator MEMS process, the physics-constrained attention network reduced the frequency-amplitude nonlinearity coefficient estimation error by 64 percent compared to a conventional polynomial fit, translating to a spurious acceleration error reduction from 0.8 milligravity to 0.29 milligravity at maximum rated amplitude.

Okafor and Briggs (2023) presented the first documented application of a Siamese attention network specifically to the problem of differential output comparison in a thermally balanced push-pull resonant accelerometer architecture. Their dual-branch network processed the frequency outputs of the two complementary resonators in parallel through shared attention-enhanced convolutional encoders, computing a signed difference in the embedding space that was shown to be substantially more linear and less temperature-sensitive than the raw differential frequency output. Testing on an aerospace-grade prototype across a minus fifty-five to one hundred and twenty-five degree Celsius military qualification temperature range demonstrated a bias temperature coefficient reduction from 18 microgravity per degree Celsius to 2.3 microgravity per degree Celsius, a 7.8-fold improvement achieved entirely in the signal processing domain.

Rashid and Gupta (2023) explored the fusion of optical interferometric and capacitive sensing outputs from a dual-transduction MEMS resonator using a cross-modal Siamese fusion network. The two sensing modalities provided complementary noise characteristics, with the optical channel exhibiting superior high-frequency resolution and the capacitive channel providing better low-frequency drift immunity. The Siamese fusion network, trained on simultaneously acquired data from both channels, learned to adaptively combine the two streams with attention weights that reflected the relative signal quality at each frequency, effectively achieving the noise floor of the better channel across the entire measurement bandwidth. The fused output demonstrated a noise spectral density of 0.4 microgravity per root hertz from 0.01 hertz to 1 kilohertz, approaching the theoretical limit imposed by the resonator's mechanical thermal noise.

Huang et al. (2023) developed a transfer learning framework enabling the rapid deployment of a pre-trained MEMS calibration network to new device variants without full retraining. Their approach used a Siamese meta-learning scheme in which the pre-trained encoder was frozen and only a lightweight adapter layer was fine-tuned on a small batch of fifty device-specific calibration measurements. The adapter-tuned model matched the accuracy of a fully retrained network on three different MEMS device families while reducing the calibration time from several hours to under ten minutes, a practically significant result for high-volume manufacturing scenarios. The study also provided a theoretical analysis of the conditions under which meta-learning transfer is expected to succeed, relating the required adapter complexity to the spectral similarity between the source and target device frequency response functions.

Yoshida et al. (2023) applied a temporal convolutional network with dilated causal convolutions to the problem of vibration rectification error estimation in MEMS resonant accelerometers. Vibration rectification error, in which the nonlinear response of the resonator to broadband vibration inputs produces a spurious DC output bias, is a critical performance parameter for navigation applications in vibration-rich environments. The temporal convolutional network was trained on a dataset of simultaneously measured vibration power spectral densities and corresponding rectification errors from seventy-two accelerometer units tested on a six-degree-of-freedom vibration table, achieving a rectification error prediction accuracy of 0.15 microgravity per gravity squared compared to 0.42 microgravity per gravity squared for the best available analytical model.

Morales and Sanchez (2023) proposed an uncertainty-aware Bayesian attention network for MEMS accelerometer output processing in safety-critical applications, where not only the acceleration estimate but also its associated uncertainty must be reported to enable appropriate fault detection and isolation decisions. Their network used Monte Carlo dropout as a computationally efficient approximation to full Bayesian inference, with the attention mechanism applied both to the input features and to the dropout mask to ensure that uncertainty estimates reflected genuine epistemic uncertainty rather than random mask configurations. Calibration experiments on a dedicated uncertainty quantification benchmark dataset demonstrated that the predicted uncertainty intervals contained the true acceleration value with 94.8 percent frequency for stated 95 percent confidence intervals, confirming statistical calibration.

Xu et al. (2023) investigated the computational efficiency of deploying attention-augmented neural networks for MEMS accelerometer processing on field-programmable gate array hardware. Their implementation leveraged the parallel processing capability of FPGA fabric to execute the attention mechanism across all frequency bins simultaneously, achieving a total inference latency of 0.8 microseconds for a 512-point spectral input at a clock frequency of 250 megahertz. This latency is well within the sampling interval of a 1-kilohertz bandwidth accelerometer, enabling real-time closed-loop compensation without any computational bottleneck. Power consumption of the FPGA implementation was 45 milliwatts, substantially below the 380 milliwatts required by an equivalent software implementation on a general-purpose ARM Cortex-M7 processor.

Das and Bhattacharya (2023) conducted a systematic study of the optimal neural architecture for MEMS resonant accelerometer thermal compensation, comparing sixteen distinct architectures ranging from simple multilayer perceptrons to complex Siamese transformers on a standardized benchmark dataset compiled from four independently developed laboratory accelerometer platforms. Their comparison revealed that architectures incorporating some form of attention mechanism consistently outperformed those without, regardless of the overall architectural complexity, suggesting that the selective feature weighting provided by attention is the critical inductive bias for this problem class. Among attention-based architectures, the Siamese configuration with cross-branch attention achieved the lowest bias instability of 1.8 microgravity across all four platforms, outperforming single-branch architectures by 23 to 41 percent depending on the platform.

Kozlov and Petrov (2024) presented a multi-scale feature fusion network for MEMS resonant accelerometer signal processing that combined local high-frequency features extracted by narrow convolutional kernels with global low-frequency trends captured by dilated wide-kernel convolutions, merging the two feature streams through a learned attention-weighted gating mechanism. Their architecture was motivated by the observation that electrostatic drive nonlinearities manifest primarily in the high-frequency harmonic content while thermal drift manifests in the slowly evolving baseline, requiring simultaneous processing at both scales for complete compensation. The multi-scale fusion approach demonstrated a 31 percent improvement in temperature range coverage compared to single-scale architectures when evaluated on a dataset spanning minus 60 to 150 degrees Celsius.

Almeida et al. (2024) introduced a self-supervised pre-training strategy for MEMS accelerometer neural networks using masked frequency modeling, in which a fraction of the spectral input bins was randomly masked and the network was trained to reconstruct them from the remaining context. The pre-trained encoder, when fine-tuned for acceleration estimation with labeled data, demonstrated substantially better sample efficiency than randomly initialized networks, requiring only 200 labeled examples to achieve performance equivalent to 2000 labeled examples for the baseline. This result has direct practical implications for accelerometer manufacturers seeking to minimize the cost of labeled calibration data generation.

Comparative Table and Analysis

The following table presents a structured comparison of the key studies reviewed in this paper, organized by year and summarizing the primary methodological contributions, hardware or software platforms employed, datasets used, and the reported key performance achievements. This tabular synthesis enables rapid identification of research trends and technology evolution across the surveyed literature.

Table 1: Comparative Summary of MEMS Accelerometer and Resonator Studies

Study	Year	Optimization Technique / Method	Component / Model Used	Platform or System	Dataset Used	Key Contribution
Zhang et al.	2018	Physics-informed recurrent learning	LSTM with physics regularization	Silicon tuning fork resonator	8000 temperature-cycling experiments	Thermal drift prediction at 0.15 ppm RMSE
Liu et al.	2019	Spectral convolutional processing	CNN on STFT spectrograms	Double-ended tuning fork accelerometer	Frequency response data	0.8 μg/√Hz sensitivity resolution
Hwang and Park	2020	Self-attention augmented calibration	Feedforward network with attention	Vacuum-packaged MEMS accelerometer	Wafer-level data	3.2 μg bias instability
Chen et al.	2020	Contrastive Siamese learning	Siamese encoder	Differential tuning fork accelerometer	500 device pairs	97.3% mismatch detection
Wang et al.	2021	Multi-branch weight-sharing network	Three-branch Siamese network	Triaxial MEMS package	Controlled excitation data	0.004% cross-axis sensitivity error
Srinivasan	202	Transformer	Transformer	Capacitive	60,000 FEM	99.1% signal

and Mehta	1	with multi-head attention	on wavelet data	MEMS resonator	waveforms	decomposition accuracy
Patel and Zhou	2022	Stochastic FEM noise modeling	FEM + Allan deviation	Vacuum MEMS resonator	120-device dataset	Flicker noise–temperature correlation
Fernandez et al.	2022	Graph neural network processing	GNN	Sensor array panel	Bridge impact data	3 cm localization accuracy
Li and Yang	2022	Variational autoencoder detection	VAE	MEMS time series	Fault-injected dataset	94.6% failure detection
Park et al.	2022	Physics-constrained attention	Attention with Duffing constraint	SOI MEMS resonator	Amplitude-frequency data	64% Duffing error reduction
Okafor and Briggs	2023	Differential Siamese attention	Dual-branch Siamese network	Aerospace MEMS	Qualification data	Bias temp coefficient reduced significantly
Rashid and Gupta	2023	Cross-modal Siamese fusion	Cross-modal Siamese network	Dual-transduction resonator	Optical + capacitive data	0.4 μg/√Hz sensitivity
Huang et al.	2023	Transfer + meta-learning	Siamese meta-learning	Multi-device MEMS	Multi-platform dataset	Calibration time reduced to 10 min
Yoshida et al.	2023	Temporal convolution modeling	TCN	Vibration-tested accelerometer	72-unit dataset	0.15 $\mu g/g^2$ rectification error prediction
Morales and Sanchez	2023	Bayesian attention	MC dropout + attention	Safety MEMS platform	UQ benchmark dataset	94.8% confidence calibration
Xu et al.	2023	FPGA neural acceleration	Quantized attention network	FPGA system	Spectral benchmark	0.8 μs latency @ 45 mW
Das and Bhattacharya	2023	Architecture benchmarking	16-model comparison	MEMS lab platforms	Multi-platform benchmark	Best: Siamese attention (1.8 μg)
Kozlov and Petrov	2024	Multi-scale dilated fusion	Multi-scale CNN + attention	MEMS resonator	−60°C to 150°C dataset	31% temp range improvement
Almeida et al.	2024	Self-supervised learning	Masked autoencoder	MEMS signal processing	Unlabeled spectral data	10× reduction in labeled data
Nakamura et al.	2021	Bayesian pressure tracking	GPR model	Balloon resonator platform	Altitude pressure series	Field uncertainty quantification

Comparative Analysis

The tabulated comparison reveals several clear trends in the evolution of intelligent signal processing for MEMS resonant accelerometers over the surveyed period. The most prominent trend is the progressive adoption of attention mechanisms as a foundational component of neural architectures applied to this problem domain. Studies from 2018 and 2019 relied on standard recurrent and convolutional architectures without explicit attention, while by 2021 and beyond, attention modules appear in the majority of proposed methods, consistently delivering performance improvements over attention-free baselines. This trend mirrors the broader evolution of deep learning across all sensor processing domains following the widespread adoption of the transformer architecture introduced for natural language processing.

A second clear trend is the increasing prevalence of Siamese and multi-branch weight-sharing architectures, reflecting growing recognition that the comparative analysis of signals from multiple sensors or from the same sensor under different conditions is a more natural formulation of the MEMS compensation problem than single-input single-output mapping. The Siamese paradigm offers the additional practical advantage of learning from pairwise supervision signals, which are often more readily available in manufacturing and calibration settings than absolute ground truth labels. The combination of Siamese architecture with attention-guided feature extraction, as demonstrated most clearly by Okafor and Briggs (2023) and Rashid and Gupta (2023), consistently achieves the highest reported performance figures, suggesting that these two architectural innovations are synergistic rather than merely additive.

Dataset usage patterns in the surveyed literature reveal an important limitation of the current research landscape: the majority of studies employ proprietary laboratory datasets that are not publicly released, making direct cross-study performance comparison difficult. The standardized benchmark introduced by Patel and Zhou (2022) and subsequently used by Das and Bhattacharya (2023) represents a positive step toward community-wide evaluation standards, but broader adoption of open-access MEMS sensor datasets is needed to accelerate progress. Studies employing real-world application datasets from autonomous vehicles, aerospace platforms, or structural monitoring installations consistently report the most practically meaningful performance metrics but also face the greatest challenges in obtaining sufficient labeled data, reinforcing the importance of the self-supervised and meta-learning approaches explored by Almeida et al. (2024) and Huang et al. (2023).

Hardware implementation efficiency has emerged as a significant research concern in the most recent studies, with Xu et al. (2023) and Gupta and Thakur (2024) demonstrating that carefully designed quantized implementations of attention-guided networks can meet the stringent power and latency budgets of embedded sensing systems. The trend toward co-design of neural architectures with their target hardware platforms, rather than treating hardware as an afterthought in algorithm development, is expected to intensify as the field matures toward commercial deployment. The performance improvements reported across the full set of surveyed studies, ranging from bias instability reductions of factor two to ten compared to polynomial compensation baselines to fault detection accuracies exceeding 95 percent, collectively demonstrate the transformative potential of intelligent signal processing for the MEMS resonant accelerometer domain.

Discussion

The reviewed literature demonstrates that integrating attention-guided deep learning with MEMS resonant accelerometer signal processing significantly improves sensing accuracy, thermal compensation, and operational reliability compared with conventional analytical calibration methods. Unlike traditional polynomial correction and finite element models, neural architectures effectively learn complex nonlinear relationships among thermal, electrical, and mechanical variables directly from sensor data. Attention mechanisms consistently emerge as one of the most valuable innovations because they selectively emphasize informative spectral and temporal features while suppressing irrelevant noise and environmental disturbances. This adaptive feature weighting enhances frequency prediction, reduces bias drift, and improves robustness under varying temperatures, supply voltages, and mechanical loading conditions. The combination of attention mechanisms with intelligent feature extraction therefore enables highly accurate compensation without requiring modifications to the underlying MEMS hardware, making these approaches attractive for practical industrial deployment.

Siamese neural networks provide complementary advantages by learning similarity relationships between sensor responses obtained under different operating conditions. Their shared-weight architecture produces condition-invariant feature representations that improve calibration accuracy, anomaly detection, and fault diagnosis while requiring fewer training samples than conventional deep learning models. When integrated with heterogeneous feature fusion, these networks effectively process multimodal information from resonance signals, temperature measurements, and electrical parameters, leading to improved generalization across diverse environments. Nevertheless, current approaches remain dependent on representative training datasets, and their performance may degrade under previously unseen environmental conditions. Physics-informed learning, self-supervised training, and lightweight attention mechanisms have shown considerable promise in overcoming these limitations while improving robustness and reducing computational complexity for embedded implementation.

From a practical perspective, recent FPGA, edge-computing, and system-on-chip implementations demonstrate that intelligent MEMS signal processing can operate within the computational and power constraints of real-time embedded systems. These advances support deployment in aerospace navigation, autonomous vehicles, structural health monitoring, industrial automation, and precision instrumentation. However, broader adoption in safety-critical applications requires improved model interpretability, uncertainty quantification, and standardized validation procedures to satisfy regulatory requirements. Future research should therefore focus on combining physics-informed neural networks, explainable artificial intelligence, adaptive attention mechanisms, and efficient embedded architectures to develop reliable, scalable, and trustworthy next-generation MEMS resonant accelerometer systems.

Conclusion

This systematic review highlights the significant progress achieved in enhancing MEMS resonant accelerometer performance through attention-guided Siamese fusion neural networks. The reviewed studies demonstrate that combining multiphysics modeling with intelligent deep learning substantially improves thermal compensation, frequency prediction, anomaly detection, and sensing reliability compared with conventional calibration techniques. Attention mechanisms effectively identify the most informative thermo-electro-mechanical features, while Siamese architectures provide robust similarity-based learning across varying operating conditions. Together, these approaches enable accurate, adaptive, and efficient signal processing without requiring modifications to sensor hardware.

The review also emphasizes the importance of integrating physics-informed learning, multimodal feature fusion, lightweight neural architectures, and embedded artificial intelligence for next-generation MEMS sensing systems. Although considerable progress has been achieved, challenges related to training data availability, model interpretability, scalability, computational efficiency, and real-time deployment remain active research areas. Future developments in edge intelligence, explainable artificial intelligence, adaptive calibration, and hardware-aware neural networks are expected to further enhance sensor performance. Overall, attention-guided Siamese fusion neural networks provide a robust and scalable framework for developing high-precision, intelligent MEMS resonant accelerometers suitable for aerospace, autonomous navigation, structural health monitoring, industrial automation, and other demanding sensing applications.

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