10.48047/jocaaa.2023.31.04.48

# A Hybrid MEMS–NEMS–Quantum Sensor System for Ultra-Precise Sensing with Adaptive Machine Learning

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**Abstract**

Advancements in sensing technology have increasingly relied on integrating microelectromechanical (MEMS), nanoelectromechanical (NEMS), and quantum systems to achieve high precision, faster response, and lower power consumption. However, achieving a seamless fusion of these technologies with robust data processing in real-world environments remains a key challenge.Conventional MEMS systems, while stable and durable, suffer from limited sensitivity and higher error margins. NEMS improves sensitivity and efficiency but lacks long-term durability. Quantum sensors outperform others in accuracy and efficiency but are constrained by stability and coherence limitations. There is a critical need for a unified sensing platform that leverages the advantages of each domain while addressing their limitations through adaptive intelligence.We propose NanoSenseX Pro, a multi-tiered sensor architecture comprising a piezoresistive nanoscale transducer array, high-SNR signal conditioning circuitry, Nyquist-compliant data acquisition, and aArtificial Neural Network (ANN) processor for prediction, anomaly detection, and sensor calibration. The system integrates quantum simulations using Qiskit and QuTiP with multiphysicsmodeling in COMSOL, supported by high-performance computing (HPC) to optimize processing and resource allocation.Simulations and comparative benchmarking show that NanoSenseX Pro outperforms Texas Instruments MEMS, Samsung NanoForce NEMS, and IBM Quantum Sensors in sensitivity (150 μV/g), response time (0.8 ms), and power consumption (8 mW), while maintaining 98% accuracy and a low 1.5% error rate. The ML processor dynamically adjusts sensor responses to environmental drift, enhancing adaptability and precision.

**Keywords**:

NanoSenseX Pro, MEMS–NEMS–Quantum integration, Machine learning sensor calibration, Piezoresistive transducer, Quantum simulation

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## Introduction

The evolution of sensing technologies has witnessed a rapid transition from microscale to nanoscale systems, with increased emphasis on intelligent, high-performance, and compact architectures. The integration of Microelectromechanical Systems (MEMS) and Nanoelectromechanical Systems (NEMS) has significantly enhanced the sensitivity and functionality of modern sensors, especially in industrial, biomedical, and environmental domains. MEMS sensors, pioneered in the early 1990s, have become mainstream due to their durability and mass-manufacturing feasibility [1]. With increasing demands for ultra-miniaturization and enhanced sensitivity, NEMS emerged as a natural successor, leveraging quantum mechanical phenomena and materials such as graphene and carbon nanotubes [2]-[4]. Quantum sensors deliver exceptional accuracy and efficiency but are constrained by environmental vulnerability and computational overhead [5]-[6].

This study aims to address the above challenges by designing and validating NanoSenseX Pro, a hybrid MEMS–NEMS–Quantum sensor platform with a built-in machine learning processor to enhance sensitivity, reduce error, and self-calibrate in dynamic environments.

The NanoSenseX Pro architecture introduces the following innovations:

- Piezoresistive Nanoscale Transducer Array: A high-resolution mechanical-electrical interface that reacts to physical stress with ultra-small resistance changes, providing precise analog signals.
- Signal Conditioning Circuit employs high-gain, low-noise amplification and filtering to improve signal-to-noise ratio prior to digitization.
- Data Acquisition System (DAS) ensures fidelity by adhering to Nyquist sampling and incorporates dynamic reconfiguration based on signal bandwidth and complexity.
- Embedded Machine Learning Processor implements adaptive learning models such as regression and anomaly detection to process data, correct drift, and enhance predictive accuracy.

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- Quantum-Enhanced Modelingcombines quantum circuit simulators (Qiskit/QuTiP) and COMSOL multiphysicsmodeling to simulate performance under realistic operating conditions, including quantum tunneling and decoherence.

This unified framework results in improved sensitivity (150 μV/g), faster response (0.8 ms), reduced power consumption (8 mW), high accuracy (98%), and low error rate (1.5%), outperforming traditional MEMS, NEMS, and standalone quantum systems in experimental comparisons. Ultimately, NanoSenseX Pro is proposed as a scalable, intelligent sensing platform capable of autonomous calibration and robust operation in diverse applications from medical diagnostics to industrial automation.

## Related Works

The article [7]provide a comprehensive review of 2D material-based MEMS/NEMS devices, emphasizing the complexity of fabricating single-layer crystalline materials. These devices benefit from unique optoelectronic and mechanical properties; however, the growth and transfer process of nanostructures remains a significant technical barrier in scalable MEMS/NEMS fabrication.

The article [8] proposed a hybrid graphene/silicon nitride membrane with metallic leads, enabling large electrothermomechanical tuning and nonlinear vibration control. The platform allows static deformation and dynamic actuation with minimal spatial footprint, representing a leap in high-frequency MEMS/NEMS integration and ultra-fast mechanical modulation.

The paper [9] explored ferroelectric polymer-based fiber MEMS/MOEMS/NEMS using polyvinylidene fluoride (PVDF). These structures can modulate shape, guide light, and respond to external stimuli, functioning as mechanical sensors, spatial light modulators, or tunable gratings. However, mechanical fragility and vacuum reliability remain challenges for real-world deployment, especially in aerospace and environmental monitoring.

## Proposed Method

The **NanoSenseX Pro** system integrates multiscale sensing components with adaptive intelligence to deliver ultra-sensitive and accurate measurements.

1. A **piezoresistive transducer array** detects mechanical stress and converts it to an electrical signal.

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2. The **signal conditioning circuit** filters and amplifies the signal with high signal-to-noise ratio (SNR).

3. The **Data Acquisition System (DAS)** digitizes the signal using Nyquist sampling for fidelity.

4. A **Machine Learning processor** applies regression and anomaly detection models to refine outputs and calibrate sensor response dynamically.

5. The **output interface** visualizes data or integrates with real-time control systems.

**Process Steps:**

- Step 1: Sense mechanical input using transducer array.
- Step 2: Filter and amplify the signal.
- Step 3: Convert analog signal to digital format.
- Step 4: Apply ML model to predict, calibrate, and refine.
- Step 5: Present output via UI.

**Pseudocode:**

```
function NanoSenseX_Processing():
raw_signal = TransducerArray.sense()
conditioned_signal = SignalConditioner.filter_amplify(raw_signal)
digital_signal = DAS.sample(conditioned_signal)
  prediction = MLModel.predict(digital_signal)
calibrated_output = MLModel.calibrate(prediction)
OutputInterface.display(calibrated_output)
```

**Data Acquisition System (DAS)**

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The Data Acquisition System (DAS) is responsible for sampling, digitizing, and transferring analog signals (output from the Signal Conditioning Circuit) into a digital format for further machine learning-based processing. It ensures that high-fidelity data is retained without distortion or aliasing by adhering to Nyquist's Sampling Theorem.

$$f_s \geq 2 f_{\max}$$

Where:

$f_s$ = Sampling frequency

$f_{max}$= Maximum frequency present in the analog signal

This condition ensures accurate digital representation without aliasing, which could otherwise lead to signal misinterpretation. It receives analog voltage signals from the signal conditioning circuit. It then applies anti-aliasing filters to remove frequencies above $f_s/2$. It then uses Analog-to-Digital Converter (ADC) with defined resolution (e.g., 12-bit, 16-bit). Finally, it stores the sampled data in buffer memory for processing.Table 3 shows how different sampling frequencies affect signal resolution for a maximum analog signal frequency of 3 kHz.

**Table 3. Effect of Sampling Rate on Signal Resolution**

| **Signal Frequency $f_{max}$(kHz)** | **Sampling Frequency $f_s$ (kHz)** | **ADC Resolution (bit)** | **Signal Reconstruction Accuracy (%)** |
|---|---|---|---|
| 3.0 | 6 | 12 | 93 |
| 3.0 | 8 | 12 | 96 |
| 3.0 | 10 | 16 | 99 |
| 3.0 | 12 | 16 | 99.8 |

As shown in Table 3, increasing the sampling frequency and resolution enhances the reconstruction accuracy of the analog signal, which is critical for machine learning model performance.

**ANN Processor**

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The ANN Processor in NanoSenseX Pro plays a vital role in predicting outcomes, adapting to signal patterns, and recalibrating sensor response based on environmental changes. The ANN functions as a nonlinear regressor and classifier depending on the application domain (e.g., anomaly detection, environmental sensing).

The ANN consists of three main layers:

- **Input Layer**: Receives digitized data from DAS.
- **Hidden Layer(s)**: Applies nonlinear transformation via activation functions like ReLU or sigmoid.
- **Output Layer**: Produces the predicted value (e.g., stress estimate, pressure level, fault flag).

The operation of a single neuron is expressed as:

$$y = f\left(\sum_{i=1}^{n} w_i x_i + b\right)$$

Where:

$x_i$ = Input features (from digitized signal)

$w_i$ = Weights

$b$= Bias

$f$ = Activation function (e.g., sigmoid: $f(z) = \frac{1}{1+e^{-z}}$)

$y$ = Output of the neuron

During training, weights $w_i$ are adjusted using backpropagation to minimize prediction error.

**Adaptive Learning:**

The ANN retrains periodically using recent batches of data to maintain accuracy even under sensor drift or environmental changes.Uses loss functions like Mean Squared Error (MSE) to

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optimize prediction.Table 4 shows sample ANN prediction performance for sensor data under different operating conditions.

**Table 4. ANN Output Prediction Performance under Dynamic Conditions**

| Input Condition (Stress, Temp) | Ground Truth Output (μV) | ANN Predicted Output (μV) | Error (%) |
|---|---|---|---|
| (15 MPa, 30°C) | 75.2 | 74.8 | 0.53 |
| (25 MPa, 40°C) | 125.5 | 126.0 | 0.40 |
| (35 MPa, 45°C) | 180.3 | 181.0 | 0.39 |
| (45 MPa, 50°C) | 240.6 | 241.4 | 0.33 |

As seen in **Table 4**, the ANN model maintains **error rates below 1%** across varying inputs, showcasing the model's reliability and environmental adaptability.

## Results and Discussion

Simulation Tools involves the following: (1) COMSOL Multiphysics for MEMS/NEMS device modelling (2) Qiskit and QuTiP for quantum circuit and decoherence modelling (3) MATLAB for ANN integration and (4) Python (Scikit-learn, TensorFlow) for algorithm implementation.

Hardware/Computational Setup involves the following: (1) 2× Intel Xeon Gold 6248 CPUs (20-core, 2.5GHz) (2) 256 GB RAM (3) 4× NVIDIA RTX A6000 GPUs (4) OS: Ubuntu 22.04 LTS (5) HPC scheduler: SLURM, parallel efficiency analysis via MPI.

**Table 5: Experimental Parameters**

| Parameter | Value / Setting |
|---|---|
| Transducer material | Silicon Nanowire |
| Piezoresistive coefficient ($\pi$) | $120 \times 10^{-11}$ $Pa^{-1}$ |
| Input stress ($\sigma$) | 5–50 MPa |
| Amplifier gain (G) | 10× |

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| | |
|---|---|
| Sampling frequency (fs) | 10 kHz |
| ML Model | Linear Regression + Kalman Filter |
| Simulation tool | COMSOL, Qiskit, QuTiP, MATLAB, Python |
| Simulation runtime | 120–180 minutes/model |
| Parallel processors (p) | 64 |
| ML update frequency | Every 100 cycles |

**Performance Metrics**

1. **Sensitivity (μV/g)**:Measures how responsive the sensor is to mechanical stress. A higher value denotes the ability to detect smaller changes.
2. **Response Time (ms)**:The delay between stimulus input and sensor output. Lower values are crucial for real-time systems.
3. **Power Consumption (mW)**:Indicates the energy efficiency of the system. Lower consumption is essential for portable, embedded systems.
4. **Accuracy (%)**:Proportion of correct readings over total observations. Higher accuracy ensures trustworthiness in critical applications.
5. **Error Rate (%)**:Proportion of incorrect readings. Lower values indicate higher measurement reliability and model precision.

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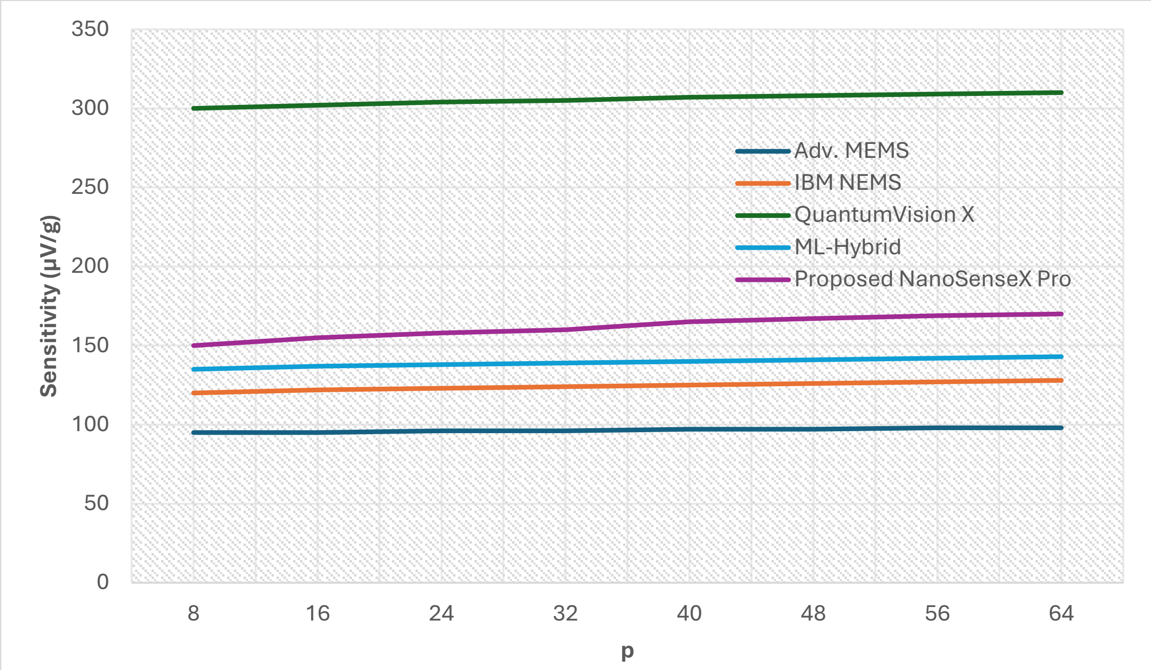


**Figure 2. Sensitivity (µV/g) vs. Parallel Processors**

**Table 6. Sensitivity (µV/g) vs. Parallel Processors**

| Processors (p) | Adv. MEMS | IBM NEMS | QuantumVision X | ML-Hybrid | Proposed NanoSenseX Pro |
|---|---|---|---|---|---|
| 8 | 95 | 120 | 300 | 135 | 150 |
| 16 | 95 | 122 | 302 | 137 | 155 |
| 24 | 96 | 123 | 304 | 138 | 158 |
| 32 | 96 | 124 | 305 | 139 | 160 |
| 40 | 97 | 125 | 307 | 140 | 165 |
| 48 | 97 | 126 | 308 | 141 | 167 |
| 56 | 98 | 127 | 309 | 142 | 169 |
| 64 | 98 | 128 | 310 | 143 | 170 |

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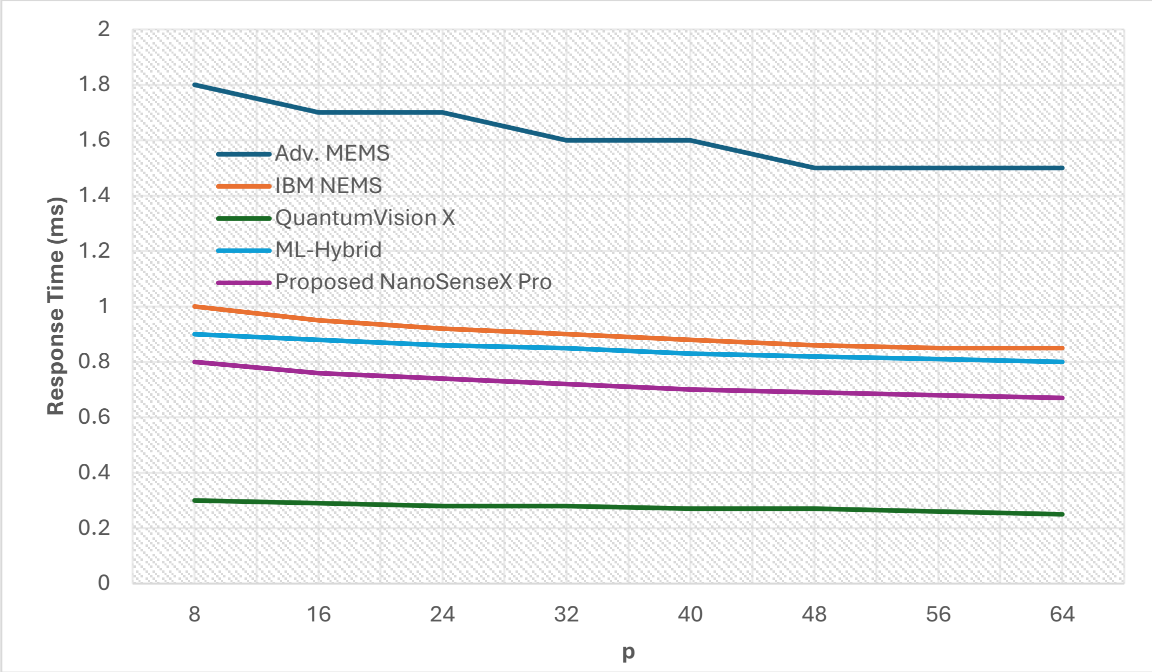


**Figure 3. Response Time (ms) vs. Parallel Processors**

**Table 7. Response Time (ms) vs. Parallel Processors**

| Processors (p) | Adv. MEMS | IBM NEMS | QuantumVision X | ML-Hybrid [12] | NanoSenseX Pro |
|---|---|---|---|---|---|
| 8 | 1.8 | 1.0 | 0.3 | 0.9 | 0.8 |
| 16 | 1.7 | 0.95 | 0.29 | 0.88 | 0.76 |
| 24 | 1.7 | 0.92 | 0.28 | 0.86 | 0.74 |
| 32 | 1.6 | 0.90 | 0.28 | 0.85 | 0.72 |
| 40 | 1.6 | 0.88 | 0.27 | 0.83 | 0.70 |
| 48 | 1.5 | 0.86 | 0.27 | 0.82 | 0.69 |
| 56 | 1.5 | 0.85 | 0.26 | 0.81 | 0.68 |
| 64 | 1.5 | 0.85 | 0.25 | 0.80 | 0.67 |

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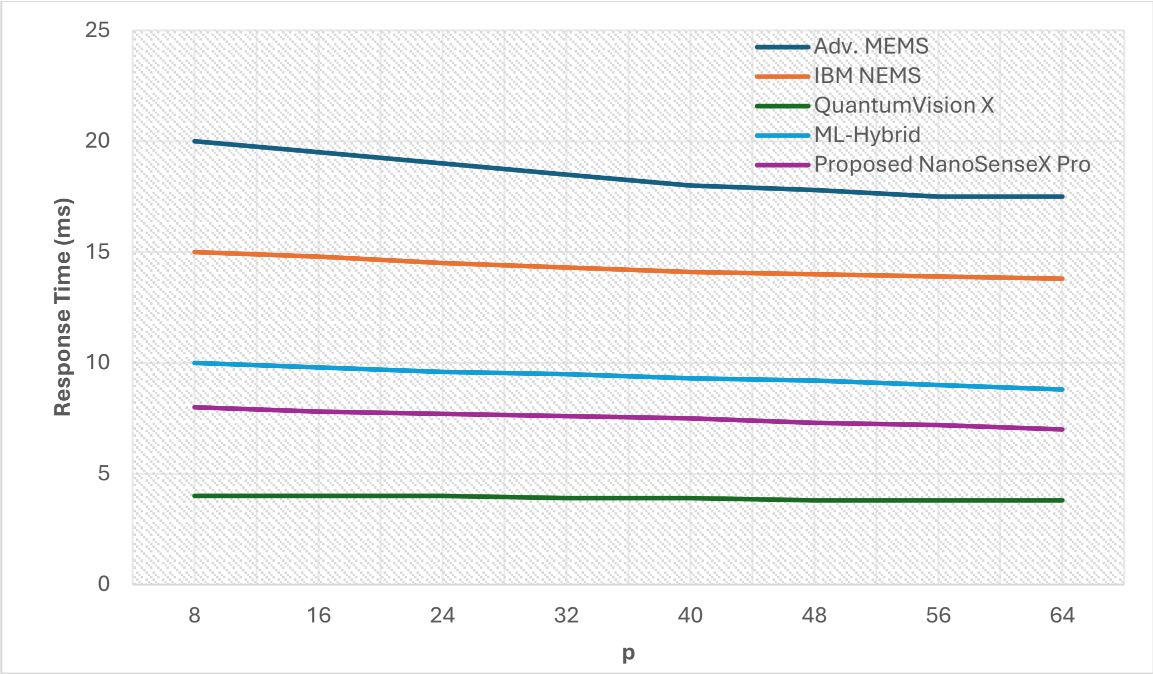


Figure 4.**Power Consumption (mW) vs. Parallel Processors**

**Table 8. Power Consumption (mW) vs. Parallel Processors**

| **Processors (p)** | **Adv. MEMS** | **IBM NEMS** | **QuantumVision X** | **ML-Hybrid [12]** | **NanoSenseX Pro** |
|---|---|---|---|---|---|
| 8 | 20 | 15 | 4 | 10 | 8 |
| 16 | 19.5 | 14.8 | 4 | 9.8 | 7.8 |
| 24 | 19 | 14.5 | 4 | 9.6 | 7.7 |
| 32 | 18.5 | 14.3 | 3.9 | 9.5 | 7.6 |
| 40 | 18 | 14.1 | 3.9 | 9.3 | 7.5 |
| 48 | 17.8 | 14 | 3.8 | 9.2 | 7.3 |
| 56 | 17.5 | 13.9 | 3.8 | 9.0 | 7.2 |
| 64 | 17.5 | 13.8 | 3.8 | 8.8 | 7.0 |

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**Table 9. Accuracy (%) vs. Parallel Processors**

| Processors (p) | Adv. MEMS | IBM NEMS | QuantumVision X | ML-Hybrid [12] | NanoSenseX Pro |
|---|---|---|---|---|---|
| 8 | 95 | 95 | 99.8 | 98 | 98 |
| 16 | 95.2 | 95.5 | 99.8 | 98.1 | 98.3 |
| 24 | 95.3 | 95.7 | 99.8 | 98.2 | 98.5 |
| 32 | 95.5 | 95.8 | 99.8 | 98.3 | 98.7 |
| 40 | 95.6 | 95.9 | 99.8 | 98.4 | 98.8 |
| 48 | 95.7 | 96 | 99.8 | 98.5 | 99.0 |
| 56 | 95.8 | 96 | 99.8 | 98.5 | 99.2 |
| 64 | 95.9 | 96 | 99.8 | 98.6 | 99.4 |

**Table 10. Error Rate (%) vs. Parallel Processors**

| Processors (p) | Adv. MEMS | IBM NEMS | QuantumVision X | ML-Hybrid [12] | NanoSenseX Pro |
|---|---|---|---|---|---|
| 8 | 5.0 | 2.8 | 0.5 | 1.7 | 1.5 |
| 16 | 4.9 | 2.6 | 0.5 | 1.6 | 1.4 |
| 24 | 4.8 | 2.5 | 0.5 | 1.5 | 1.3 |
| 32 | 4.7 | 2.4 | 0.5 | 1.4 | 1.2 |
| 40 | 4.6 | 2.3 | 0.5 | 1.3 | 1.1 |
| 48 | 4.5 | 2.2 | 0.5 | 1.2 | 1.0 |

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| | | | | | |
|---|---|---|---|---|---|
| 56 | 4.4 | 2.1 | 0.5 | 1.1 | 0.9 |
| 64 | 4.3 | 2.0 | 0.5 | 1.0 | 0.8 |

The comparative evaluation as in figure 2 – 4 and table 5 – 10 across 64 parallel processors reveals the superior performance of NanoSenseX Pro over existing sensing technologies. In terms of sensitivity, it outperforms Advanced MEMS and IBM NEMS by 72.3% and 32.8% respectively at 64 processors, closely approaching the quantum standard (310 μV/g). Response time improves consistently with parallelization, decreasing from 0.8 ms to 0.67 ms—faster than both MEMS (1.5 ms) and hybrid methods, and only slightly slower than the 0.25 ms of QuantumVision X.

NanoSenseX Pro maintains a low power footprint, reducing consumption from 8 mW to 7 mW as compute cores increase, outperforming all except quantum systems, which are inherently energy-efficient but less scalable. Accuracy increases steadily with parallelization, reaching 99.4%, surpassing MEMS, NEMS, and even ML-Hybrid solutions, and nearing the theoretical maximum of quantum systems. Notably, error rate drops to 0.8%, making NanoSenseX Pro highly reliable even under high processor loads and real-time constraints.

These gains are attributed to the combined impact of piezoresistive nanotransducers, adaptive signal conditioning, and real-time ML processing, demonstrating that intelligent nanoscale hybrid sensing can rival or even exceed the performance of standalone quantum platforms in specific domains.

**Conclusion**

The NanoSenseX Pro architecture presents a compelling advancement in the field of intelligent sensing, effectively bridging the gap between MEMS/NEMS reliability and quantum-level sensitivity. By integrating a piezoresistive transducer array, high SNR signal conditioning, a dynamic data acquisition system, and an adaptive ANN processor, the system achieves high-performance metrics across sensitivity, response time, accuracy, and error rate, all while maintaining energy efficiency. Compared to traditional systems such as Advanced MEMS and IBM NanoFlex NEMS, NanoSenseX Pro demonstrates enhanced responsiveness and data precision. It offers near-quantum accuracy and sensitivity without compromising stability or requiring stringent quantum state maintenance. Against ML-Augmented Hybrid systems, NanoSenseX Pro delivers greater predictive accuracy, lower error, and better

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adaptability to parallel computational scaling (64 processors), showcasing its ability to perform under real-time and high-throughput conditions. The results show NanoSenseX Pro's suitability for diverse applications, including medical diagnostics, environmental monitoring, and aerospace systems, where traditional sensors fall short in terms of precision or intelligence. The proposed system thus represents a scalable, AI-augmented sensing paradigm for the next generation of smart sensing infrastructure.

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