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Energy-Efficient Wireless Accelerometer Using Hybrid Edge–Central AI for High-Tech Machine Condition Monitoring: A Feasibility Study

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Abstract – **Machine condition monitoring and predictive maintenance are crucial technologies in modern industrial settings. Wireless sensor networks (WSNs) are commonly used to gather machine data with high flexibility and minimal installation effort. However, traditional WSN approaches that periodically or selectively transmit raw data either lack predictive capability or consume excessive energy. Furthermore, conventional static Edge-AI models running entirely on sensor nodes struggle to adapt to dynamic and complex industrial conditions due to limited labelled failure data and unpredictable machine dynamics. In this paper, we propose and evaluate a hybrid edge-central AI architecture. In this approach, sensor nodes perform the feature extraction as the first layer of the AI model, while deeper adaptive model layers operate at the central base station. This approach reduces energy consumption by limiting radio transmissions and enabling the use of complex, adaptive AI models. We validate the proposed architecture by implementing a set of common features on a typical ARM Cortex-M4 microcontroller used in wireless sensor nodes. We target the architecture of our previously developed wireless 1 kS/s (kilo-sample per second) accelerometer. Results demonstrate that these features can be computed in only 32.5 ms and consume 32.43 µW. This represents a significant energy saving compared to raw measurement transmission (686.4 µW), highlighting the effectiveness and feasibility of our hybrid approach for industrial monitoring.**

Keywords – **wireless sensor networks; vibration monitoring; MEMS accelerometers; condition monitoring; industrial sensing.**

I. Introduction

In advanced industrial environments such as semiconductor manufacturing, continuous and precise monitoring of machine dynamics is vital to optimize productivity and minimize downtime. Machine condition monitoring (MCM) and predictive maintenance are thus critical for modern industries operating high-value equipment, such as semiconductor tools and precision robots. Real-time analysis of vibration, sound, and other parameters can detect early signs of wear or faults, enabling proactive maintenance, enhancing equipment availability, safeguarding product quality, and reducing operational costs.

Wireless sensor networks (WSNs) have become an attractive solution for deploying MCM systems due to their flexibility, ease of installation, and minimal infrastructure modification. Battery-powered wireless vibration sensors are particularly valuable as mechanical faults typically manifest themselves through subtle changes in vibration spectra.

In our previous research [1], we developed and validated a wireless accelerometer network on a wafer-handler robot arm, demonstrating its reliability in industrial environments. We further enhanced the system by achieving better than 100 µs synchronization accuracy between the sensor nodes, enabling concurrent, phase-accurate vibration measurements [2]. However, the approach of transmitting raw sensor data directly to a central station leads to high energy consumption and rapid battery depletion.

To address these limitations, edge-AI solutions have emerged, focusing on compressing complex AI models to operate directly on microcontrollers. Recent examples include: the EdgeCog platform [3], which compresses convolutional neural networks (CNNs); real-time CNN-based fault detection on NVIDIA Jetson TX2 boards [4]; and lightweight CNN implementations on STM32-based nodes [5]. Montes-Sanchez et al. demonstrated predictive maintenance using recurrent neural networks (RNN) on similar edge platforms [6]. Morenas et al. also showcased fault diagnosis using decision trees, random forests, and support vector machines implemented on Arduino-based systems [7].

Despite these advances, deploying edge-AI in high-tech industries remains challenging for two primary reasons. First, effective AI models typically require extensive, well-labelled datasets, often unavailable for specialized, rapidly evolving high-tech machinery. Second, many such systems are newly designed and only fully understood post-deployment. Updating fault detection models then becomes problematic, requiring cumbersome physical access to update sensor nodes.

We propose a hybrid edge-central AI architecture as a solution. In this approach, sensor nodes execute fixed, lightweight feature extraction, significantly reducing energy consumption and communication overhead. Deeper adaptive layers, such as Long-Short-Memory (LSTM) or fully connected networks, operate at the central station, allowing easy updates and retraining. This hybrid method leverages the energy efficiency of edge processing while maintaining the flexibility and adaptability necessary for high-tech industrial environments.

The main contribution of this paper is a feasibility study demonstrating the selection and implementation of computationally efficient yet meaningful vibration features on a resource-constrained ARM microcontroller.

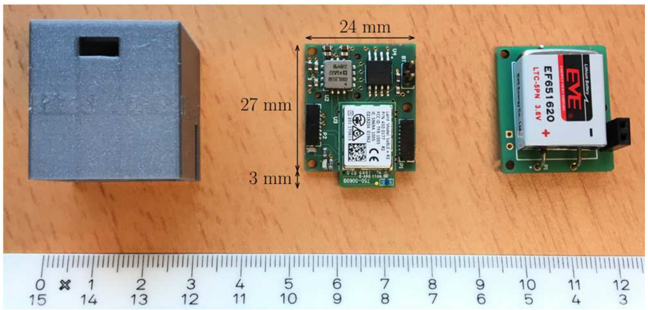

Fig. 1. Housing, sensor board, and battery [8].

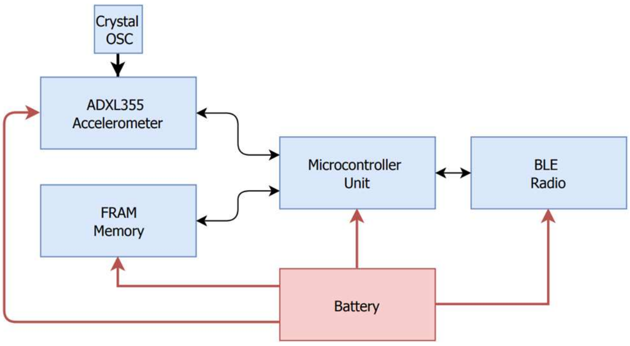

Fig. 2. Architecture of the wireless sensor node [2].

Additionally, we outline a conceptual design for the adaptive AI model to run on a central station; however, detailed model training for specific applications is beyond this paper's scope.

The paper is structured as follows: Section II outlines the wireless sensor node architecture and hardware baseline. Section III describes the lightweight vibration features extracted by sensor nodes. Section IV presents experimental power consumption results for these features. Section V discusses the proposed hybrid AI model architecture, and Section VI provides concluding remarks.

II. Sensor Node Architecture

Fig. 1 depicts the sensor node hardware, which we developed in our previous work [1], and we consider it as a baseline to build a hybrid edge-central AI fault detection solution.

This compact (30 mm × 35 mm) sensor node is designed specifically for wireless vibration monitoring. In addition to the battery, this device consists of four primary components (see Fig. 2).

- *ADXL355 MEMS Accelerometer:* A three-axis accelerometer with ultra-low noise characteristics, supporting synchronous operation through external clock inputs and digital filter resets, operating synchronously at a 1.024 MHz reference frequency.
- *Microcontroller Unit:* managing tasks including sensor data collection, temporary storage, and wireless transmission.
- *4-Mbit FRAM Memory:* Offers fast, non-volatile data storage to buffer sensor information, protecting against data loss during communication interruptions.
- *Clock Source:* Optionally utilizes a high-precision 0.3 ppm oven-controlled crystal oscillator for stringent timing accuracy or synchronization between the nodes**.**

III. Feature Extraction on the Edge for Machine Condition Monitoring

In machine condition monitoring, the edge system (the sensor node) must extract meaningful features from sensor signals using limited computational resources. This section presents lightweight, informative features suitable for implementation on microcontroller-based nodes. These features are computed locally and transmitted to a central station for higher-level neural network processing. All features discussed are derived from a section of a discrete-time vibration signal $x = \{x_1, x_2, \dots, x_n\}$.

Each of these features was specifically selected for use in sensor nodes based on their:

- Computational efficiency and suitability for implementation on fixed-point MCUs.
- Ability to effectively characterize a wide range of mechanical fault signatures when used in combination.

Together, these features form a robust descriptor vector that can be periodically transmitted to the base station for further analysis using deep learning models.

A. *Peak Amplitude*

Peak Amplitude is the maximum absolute value of a signal represents the largest excursion from the baseline. It is a simple but effective indicator of transient or impulsive behavior in machine vibrations.

$$x_{peak} = \max(|x_1|, |x_2|, \dots, |x_a|) \quad (1)$$

In machine condition monitoring, the peak amplitude feature can detect sudden increases that may indicate impacts, faults, or collisions. Compared to statistical features, peak amplitude is more sensitive to rare, high-magnitude anomalies. However, since peak amplitude alone does not account for the duration or frequency of these events, it should be used alongside other features to achieve reliable monitoring performance. Due to its simplicity, it can be computed in real-time with negligible memory or computational load.

The most widely used measure of signal power and energy content, and it provides a quantitative assessment of vibration intensity.

B. Root Mean Square (RMS)

RMS is the most widely used measure of signal power and energy content, and it provides a quantitative assessment of vibration intensity.

$$x_{RMS} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2} \quad (2)$$

In machine monitoring, the RMS value increases as overall vibration energy rises, often due to wear, imbalance, or misalignment. Compared to peak amplitude or kurtosis, RMS is less sensitive to isolated spikes, making it effective for identifying consistent changes in system performance. As a result, RMS is commonly used as a baseline indicator in threshold-based alert systems. It provides a stable and noise-resistant measure of signal power, making it particularly valuable for monitoring rotating equipment and motors.

C. Skewness

Skewness is a statistical measure that describes the degree of asymmetry of a signal's amplitude distribution around its mean. For an accelerometer attached to a machine, skewness provides valuable insight into the directional bias or nonlinearity of dynamic behaviors. In normal operation, machines tend to generate signals that are approximately symmetric. A deviation from this symmetry can indicate faults like looseness, early bearing failure, impulsive shocks, structural damping, or load-direction changes. For a discrete-time signal $x = \{x_1, x_2, \dots, x_n\}$, it is calculated as:

$$Skewness = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{x_i - \mu}{\sigma}\right)^3 \tag{3}$$

where μ and σ are the mean and standard deviation of the signal, respectively, Skewness is lightweight to compute, especially when using fixed-point arithmetic, and is suitable for real-time feature extraction on microcontroller-based edge nodes.

D. Zero-Crossing Rate (ZCR)

This parameter measures how frequently a time-domain signal changes signs within a given time frame. It provides a computationally lightweight method for approximating the dominant frequency characteristics of a vibration or acoustic signal without performing a full frequency-domain analysis.

Formally, ZCR can be defined as follows:

$$ZCR = \frac{1}{n-1}\sum_{i=1}^{n-1}|sgn(x_{i+1}) - sgn(x_i)| \tag{4}$$

where the sign function, $sgn(x_i)$, is given by:

$$sgn(x) = \begin{cases} -1, & x < 0 \\ 1, & x \geq 0 \end{cases} \tag{5}$$

In machine monitoring, ZCR helps detect changes in rotational speeds or resonant frequencies. It can also identify abnormal operating conditions characterized by frequency shifts, such as looseness or imbalance.

Given its computational simplicity, ZCR provides frequency-domain insights without the computational complexity of FFT-based analysis; it complements amplitude-based features like RMS and Peak.

E. Kurtosis

This parameter is a higher-order statistical measure that reflects the "tailedness" or sharpness of a signal's amplitude distribution. In machine condition monitoring, kurtosis is highly sensitive to impulsive, non-Gaussian signal components often associated with mechanical faults such as bearing wear, cracks, or looseness. Kurtosis (K) is computed mathematically as:

$$\text{Kurtosis} = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{x_i - \mu}{\sigma}\right)^4 \tag{6}$$

where μ is the mean and σ is the standard deviation of the signal $x = \{x_1, x_2, \dots, x_n\}$. A kurtosis value around 3 indicates a normal (Gaussian) distribution. Kurtosis larger than 3 signifies a heavy-tailed distribution with more frequent extreme values, commonly associated with impulsive events or defects. Kurtosis smaller than 3 suggests a flatter distribution, which is rare in machine vibrations unless signal clipping or saturation occurs.

IV. Experimental Results

We implemented the algorithms for each feature on a Nucleo-WB55 evaluation board, representing a typical MCU commonly utilized in wireless sensor nodes [9]. This evaluation board contains a Cortex-M4-based STM32WB55 MCU, capable of multi-protocol radio communication in the 2.4 GHz band. The feature-extraction algorithms were executed on synthetic data representing a 1-second sample collected at 1 kSps from a three-axis accelerometer, with each axis producing 16-bit integer data. The Peak and ZCR features yield 16-bit integer results, while the remaining features produce 32-bit floating-point outputs. Energy consumption measurements were performed using a Nordic Power Profiler Kit II [10].

Tables 1 and 2 summarize the efficiency gains from implementing feature extraction on an STM32WB55 MCU for wireless sensor nodes. As shown in Table 1, the computational overhead for computing vibration descriptors is minimal, with a total computational load of 32.5 ms. ("Exe. Time" is the total execution time for all axes). The test is conducted with a 2.75V power supply. In the last column, the average power consumption of the MCU is reported, assuming each of these five features needs to be calculated once per second.

Table 1. Power Consumption for Different Features

Feature	Exe. time (ms)	Current cons. (µA)	Avg. power (µW)
Peak	2.7	316.5	2.35
RMS	3.4	335.2	3.13
ZCR	4.5	318.3	3.94
Skewness	10.8	346.6	10.29
Kurtosis	11.1	348.9	10.65
Total	**32.5**	**-**	**30.37**

Table 2 demonstrates the power consumption benefit of transmitting feature vectors rather than raw sensor data. Transmitting raw data (48 kb/s) consumes about 686 µW, whereas transmitting the reduced descriptor set, 144 bit/s (4×32 + 16), requires merely 2.06 µW. Overall, including computational overhead, this approach achieves a significant reduction in energy consumption (32.43 µW vs. 686.4 µW).

Table 2. Power Consumption for Raw Data vs. Feature Transmission

Method	Data Size (bit)	Trans. power (µW)	Total power (µW)
Raw data [1]	48000	686.4	686.4
5 features	144	2.06	32.43

V. Discussion and Future Work

The extracted features form a robust descriptor vector that can be periodically transmitted to the base station for further analysis using deep learning models. These computationally inexpensive features significantly reduce wireless transmission bandwidth and energy consumption. These feature extraction algorithms on edges are fixed and lightweight. Furthermore, the rest of the fault detection model on the base station side can be elaborate and flexible.

We propose the following distributed AI Model (Fig. 3). The first layer of the model is implemented at the edge, and the rest will be located at the base station.

1) **Feature Extraction layer:** The first layer generates the descriptor vector that will be transmitted wirelessly to the base.
2) **Long Short-Term Memory (LSTM):** to analyze and capture temporal dependencies and sequential patterns. It processes the sequence of descriptor vectors and returns a sequence of outputs.
3) **Second LSTM layer:** processes the output of the first LSTM further to extract more abstract features or capture higher-level temporal patterns;
4) **Fully-Connected Layers:** Dense layers to interpret extracted temporal features;
5) **Output Layer:** A softmax classifier (for condition classification) or linear regression layer.

The detailed structure of the base station model, such as the number of units, dropout, number of epochs, etc., shall be tuned based on a proper hyperparameter tuning algorithm according to the data set and application.

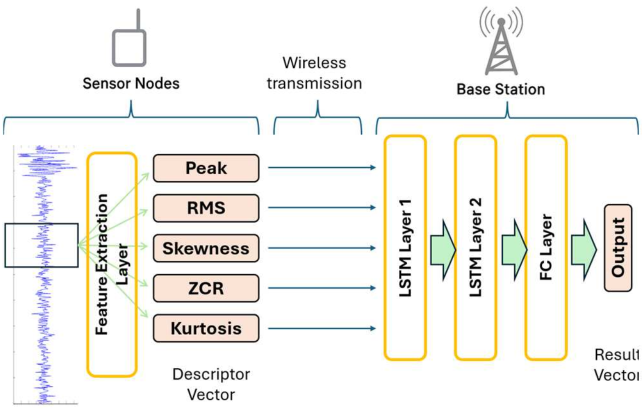

Fig. 3. The proposed architecture of the AI model.

This proposed hybrid architecture logically aligns with practical constraints and application requirements. The statistical features extracted at the edge capture essential characteristics of machinery health signals, effectively condensing complex waveform data into a minimal set of meaningful indicators. These features are widely acknowledged in the literature as reliable fault indicators in vibration-based condition monitoring.

The subsequent LSTM-based temporal model at the base station is justified by the sequential nature of machinery data, where temporal correlations play a critical role in fault progression and detection. The recurrent structure of LSTM networks allows for capturing and interpreting temporal patterns effectively, thus enabling accurate fault detection and diagnosis.

Testing and empirical evaluation of this model fall outside the scope of this paper and are reserved for future work.

VI. Conclusion

In this paper, we presented a hybrid AI approach combining edge computing and central processing. In this model, sensor nodes calculate five simple vibration features, while more complex adaptive models run at the central station. The sensor-level computation, implemented on an ARM Cortex-M4 processor, consumed only 25.8 µW, significantly reducing energy consumption and communication traffic compared to transmitting raw data. Despite this reduction, the chosen features maintained high accuracy in fault detection using advanced models like LSTM and fully connected networks at the central node. This approach extends sensor battery life and allows easy updates or expansions of the central models without altering sensor hardware, making it beneficial in industrial environments where data is limited and conditions change rapidly, like in hi-tech industries. Future research will implement and investigate the performance of the whole AI model and the integration of multiple sensor types to improve performance and efficiency further.

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