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Operation of digital Micro-Electromechanical sensor technology in turbomachinery diagnostics systems

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Abstract Rotating machine failures cause major production losses, representing 15–60% of operation costs. Predictive maintenance, particularly vibration analysis, is widely used to detect and prevent faults. While traditional vibration sensors are effective, their high cost limits broad adoption, especially in cost-sensitive industries. This study explores the feasibility of micro-electromechanical systems (MEMS)-based accelerometers for turbomachinery vibration monitoring. Controlled laboratory tests with a modal exciter evaluated MEMS sensor performance, focusing on signal clarity, frequency response, and data acquisition. Results were compared to those from an industrial-grade velocity transducer (Bently Nevada Seismoprobe). The results show that MEMS accelerometers can provide sufficiently accurate vibration measurements, supporting their use as cost-effective alternatives for basic condition monitoring. This study highlights the ability of MEMS sensors to deliver acceptable signal quality for practical vibration analysis, with implications for their use in broader industrial applications.

Keywords: vibration measurement, MEMS accelerometers, low-cost sensors, signal quality, spectral analysis.

1. Introduction

The reliability and efficiency of rotating machinery, particularly turbomachinery, profoundly influence industrial operations due to their vital role in energy conversion and production processes. Equipment failure in rotating machinery frequently results in substantial operational disruptions, significantly increasing maintenance costs and accounting for approximately 15% to 60% of total production expenses. To mitigate these impacts, predictive maintenance has emerged as an essential strategy, allowing early detection of potential faults, thereby substantially reducing downtime, lowering repair expenditures, and improving overall machine availability and operational efficiency [1, 2]. However, implementing such maintenance frameworks requires accessible and scalable diagnostic tools, particularly for vibration-based monitoring systems. Among predictive maintenance techniques, vibration-based condition monitoring is widely recognized as one of the most effective methods for detecting faults in turbomachinery [3].

Vibration analysis allows the identification of common issues such as imbalance, misalignment, bearing defects, and looseness by interpreting specific frequency signatures and patterns in the vibration data [4–6]. Traditional vibration monitoring systems predominantly use piezoelectric accelerometers or other high-grade industrial sensors, known for their accuracy and reliability under harsh conditions. However, these sensors often involve substantial economic costs, limiting their widespread deployment across machinery fleets, particularly within industries sensitive to budget constraints [7, 8]. This economic constraint has led to growing interest in low-cost alternatives. Recent advancements in micro-electromechanical system (MEMS) technology present a viable solution for cost-effective vibration monitoring. MEMS accelerometers offer numerous advantages, including low cost, compactness, digital compatibility, and suitability for large-scale deployment in wireless sensor networks [9]. Their potential in replacing traditional vibration sensors has been explored across diverse industrial applications, ranging from rotating machinery diagnostics to structural health monitoring of large-scale infrastructure such as wind turbine towers [9–12].

Extensive research has emphasized the capabilities and practical applications of MEMS accelerometers in vibration analysis and diagnostics. For instance, D'Emilia and Natale [13] investigated the accuracy and diagnostic reliability of MEMS sensors, confirming their effectiveness for industrial condition monitoring. Ye et al. [14] similarly demonstrated MEMS accelerometer efficacy in pavement vibration analysis, expanding their applicability beyond traditional industrial settings. Furthermore, integration with Internet-of-Things (IoT) systems has enabled remote, real-time monitoring capabilities, enhancing predictive maintenance programs and aligning with Industry 4.0 objectives [8].

Studies exploring specific industrial scenarios highlight the versatility and effectiveness of MEMS-based systems. For example, Aswin et al. [15] implemented an online vibration monitoring system using 3-axis MEMS accelerometers, successfully demonstrating their potential for continuous monitoring of rotating machinery. Mystkowski et al. [16] designed and evaluated a low-cost vibration-based machine monitoring system using MEMS accelerometers to assess the health condition of agricultural machinery, demonstrating comparable performance to commercial systems in both time and frequency domain analyses, thereby validating its feasibility for cost-effective condition monitoring in agricultural machinery. More comparative studies between MEMS and traditional wired sensors have also revealed similar diagnostic capabilities, thus validating MEMS sensors as reliable alternatives [17, 18]. Wireless MEMS sensor networks, in particular, have gained significant traction for their ability to provide continuous condition monitoring of rotating machinery in industrial environments [19]. Additionally, MEMS-based vibration analysis has benefited significantly from advanced analytical techniques and algorithms. Approaches such as instantaneous spectral entropy have been successfully employed for fault detection in wind turbines [20]. The use of domain adaptation techniques in vibration-based diagnostics allows for enhanced fault detection across different operational conditions, making MEMS sensors more adaptable for real-world applications [21]. Machine learning algorithms, including sparse Bayesian methods and optimal symbolic entropy techniques, have further improved fault diagnosis accuracy, enabling timely and informed decision-making in predictive maintenance [6, 22–24].

This study focuses on evaluating the signal quality and spectral performance of digital MEMS accelerometers under controlled vibration conditions. Rather than presenting a complete diagnostic framework or reliability testing over time, the aim is to validate the suitability of MEMS sensors for basic vibration monitoring tasks. Successful demonstration of MEMS sensor effectiveness could significantly enhance the adoption of the sensors in real time vibration diagnostics. Experimental assessments using modal exciters and vibration calibrators were performed to measure frequency response, signal clarity, and sampling behavior under controlled vibration conditions. The study employs spectral analysis techniques to assess signal quality, frequency response, and diagnostic capability. A comparative analysis with industrial-grade accelerometers and professional vibration analyzers provides further validation of the feasibility of MEMS-based solutions. The findings highlight the potential of MEMS sensors in revolutionizing condition monitoring, improving operational efficiency, and reducing maintenance costs across various industrial sectors, particularly in the context of low-cost, scalable monitoring solutions. While long-term field reliability is beyond the scope of this study, the findings contribute to understanding the conditions under which MEMS sensors can serve as viable tools for vibration analysis in industrial settings.

2. Materials and methods

2.1. Sensor selection

Micro-electromechanical system (MEMS) accelerometers were selected to evaluate their effectiveness in vibration measurements. An overview of the MEMS accelerometers used for vibration monitoring in recent experimental studies is presented in Tab. 1. The most commonly used sensors include accelerometers from the ADXL series, ranging from the cheapest ones (ADXL335) to more expensive and sophisticated modules. Out of the showcased MEMS accelerometers, three were selected: ADXL355 (a 3-axis digital sensor with 20-bit resolution), ADXL103 (a single axis analog sensor), and LSM6DSR (an ultra-low-power 3-axis digital sensor with 16-bit resolution). ADXL355 was chosen due to its high resolution and low noise density; however it is the most expensive of the three sensors. ADXL103 was chosen in order to assess the benefits of an analog output, which can offer continuous signal without the need for digital conversion. Lastly, LSM6DSR was chosen as an economical 3-axis digital accelerometer with adequate resolution and bandwidth for general-purpose vibration monitoring.

While MEMS sensors offer a cost-effective and compact solution for vibration measurement, their parameters are highly sensitive to temperature changes and can drift over time. These factors necessitate regular calibration and compensation techniques to achieve reliable results. Although many research articles may not emphasize these challenges, they are important considerations when implementing MEMS vibration sensors in industrial environments.

Table 1. Overview of MEMS accelerometers commonly used for vibration measurements in literature (**bold text -** MEMS accelerometers used for research).

Sensor	Sensitivity [mV/g]	Bandwidth [Hz]	Noise density [g/√Hz]	Application
ADXL103 [25]	960 - 1040	0.5 - 2500	110	Diagnosis of friction on an unbalanced rotor
ADXL1001, ADXL1002 [12]	16, 40	22 000, 10 000	4250, 25	Bearing fault diagnosis, condition monitoring of electrical motors in the food industry
ADXL202 [17]	140 - 200	6000	200	Shaft misalignment detection in a bearing test rig
AD22035 [22]	94 - 106	0.5 - 2500	230	Bearing fault diagnosis
ADXL335 [26, 27]	270 - 330	0.5 - 1600	150 - 300	Tool condition monitoring in turning, identification of stator winding insulation faults
ADXL345 [15]	210 -1650	0.1-3200	293[1]	Online vibration monitoring system for rotating machinery
ADXL354 [19]	100 - 400	1500	20	Vibration monitoring of a test rotor
ADXL355 [8, 11]	101 - 475[2]	1-1000	25	Measurement of vibrations of a rotating paper machine roll, health monitoring of wind turbine towers
ADXL356 [16]	20 - 80	2400	75-110	Vibration measurement for hay rotary tedder
LSM6DSR [13]	56 - 450[3]	1.6 - 3334	60	Condition monitoring of a cutting unit and mechatronic system test bench

[1] Noise density calculated assuming ODR = 100 Hz for ±2g, 10-bit resolution as specified in [28].
[2] Sensitivity calculated assuming a 20-bit ADC and reference voltage of 1.8V.
[3] Sensitivity calculated assuming a 16-bit ADC and reference voltage of 1.8V.

For instance, the ADXL355 accelerometer exhibits a sensitivity change due to temperature of ±0.01%/°C [28], potentially causing proportional measurement errors if not compensated. Over extended periods, the ADXL355 may experience aging effects that contribute to gradual bias drift, with reliability being predicted for a 10 year life (including shifts due to temperature cycling, velocity random walk, temperature hysteresis etc.) in its datasheet. MEMS sensors are also characterized by cross axis sensitivity, calibration drift increasing over the lifetime, and limited dynamic range. Those caveats can be reduced by selecting higher grade MEMS sensors (e.g. the ADXL355, characterized by low drift and low noise), but should be nonetheless taken into the account when designing a vibration monitoring system to ensure data accuracy and long-term stability. Proper sensor selection, environmental compensation, and routine recalibration are essential steps to mitigate these issues and maintain reliable performance in demanding industrial applications.

2.2. Experimental setup

To evaluate the performance and reliability of the MEMS sensors, as well as compare them to commercially available industrial-grade sensors, vibro-acoustic measurements using VEB ROBOTRON-MESSELEKTRONIK model 11077 vibration exciter (Fig. 1) were performed. Subjecting the accelerometers to controlled vibrations and comparing their output with the reference signal allows the assessment of the ability of the measurement system to be used in monitoring and diagnostics of rotating machinery.

The vibration level of the shaker can be controlled by adjusting the electric current intensity. The measurement system consisted of the vibration shaker, a PL-1402 power amplifier, and an E-MU 0204 sound card, with the test signal being prepared using the Multitone Analyzer software. The sound card was used to capture and digitize the signals generated by analog sensors (with the signal from the digital MEMS sensors being saved directly to a SD card) but also to play the test signal itself. The ADXL103 was mounted on a custom-designed printed circuit board (PCB) connected to the EMU 0204 audio interface for signal digitization and spectral analysis.

A laboratory-grade Bently Nevada Seismoprobe velocity transducer was used to check the signal quality. The sensor is designed to measure absolute vibration and uses moving-coil technology - the output voltage is proportional to the vibration velocity. The vibration amplitude was set to be lower than the smallest velocity threshold defined in ISO 10816 (V_{RMS} =0.71 mm/s) for every test case in order to evaluate whether the sensors can accurately measure small vibrations characteristic for new machine condition. The test signals used for all sensors were sine waves with frequencies between 20 Hz and 2 kHz, since the typical frequency response of the sensor specifies a good output signal quality for up to 1 kHz.

Figure 1. Vibration shaker with the Bently Nevada Seismoprobe transducer.

2.3. Data processing

The noise and dynamic performance of each sensor was quantified using two metrics - signal-to-noise-ratio (SNR) and total harmonic distortion (THD). Total harmonic distortion is defined as the ratio of the root mean square value of all harmonics of a signal to the RMS value of the fundamental frequency, as shown in:

$$THD = \frac{\sqrt{V_2^2 + V_3^2 + V_4^2 + \cdots + V_n^2}}{V_1}, \tag{1}$$

where V_1 is the RMS value of the fundamental frequency component, and V_n is the RMS value of the n-th harmonic frequency.
THD can also be determined based on the SINAD (Signal-to-Noise-and-Distortion-Ratio) and SNR values according to:

$$THD = -10\log_{10}(10^{-\frac{SINAD}{10}} - 10^{-\frac{SNR}{10}}), \tag{2}$$

while SNR is defined as the ratio of the power of a signal to the power of background noise. It quantifies the quality of a signal by comparing its strength to the level of unwanted noise, as seen in:

$$SNR = 10\log_{10}\frac{P_{signal}}{P_{noise}}, \tag{3}$$

where P_{signal} is the average power of the signal, and P_{noise} is the average power of background noise.
SINAD is defined as the ratio of the power of the fundamental signal to the combined power of noise plus all harmonic distortion components:

$$SINAD = 10\log_{10}\frac{P_{signal} + P_{noise} + P_{distortion}}{P_{noise} + P_{distortion}}, \tag{4}$$

where $P_{distortion}$ is the average power the distortion component.

In the case of the Bently Nevada Seismoprobe velocity sensor and ADXL103, the THD and SNR values were acquired directly during the measurements using Multitone Analyzer software. In the case of ADXL355 and LSM6DSR, the THD and SNR values were calculated analytically based on the time-domain signal by applying Fourier analysis to extract harmonic components and noise levels.

3. Results

The THD and SNR values, presented as a function of signal frequency, are presented in Fig. 2 and Fig. 3, respectively. Overall, ADXL355 provides the best output signal quality of all the tested MEMS sensors when taking THD and SNR values into account. The ADXL355 sensor reaches THD values comparable to the ones in the Bently Nevada Seismoprobe output signal (reaching lower values than the velocity transducer signal at frequencies over 100 Hz).

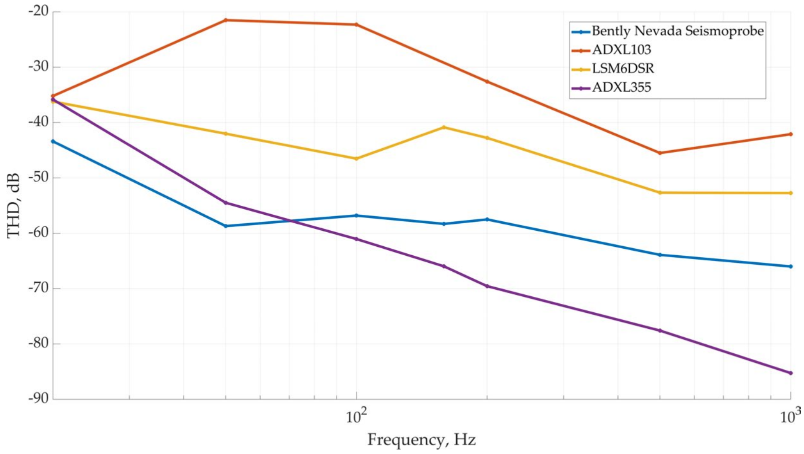

Figure 2. Comparison of THD values as a function of signal frequency for all tested sensors.

The ADXL355 shows a consistently decreasing THD value, and reaches values as low as -80 dB at higher frequencies. The ADXL103 exhibits the highest THD, remaining around -30 dB across most of the frequency range, indicating significant harmonic distortion. As a velocity transducer, Bently Nevada Seismoprobe is optimized for vibration measurement, featuring better mechanical damping and analog signal conditioning, thus reducing harmonics. On the other hand, the ADXL355 is a high-performance MEMS accelerometer with low noise and low distortion, making it well-suited for precision applications.

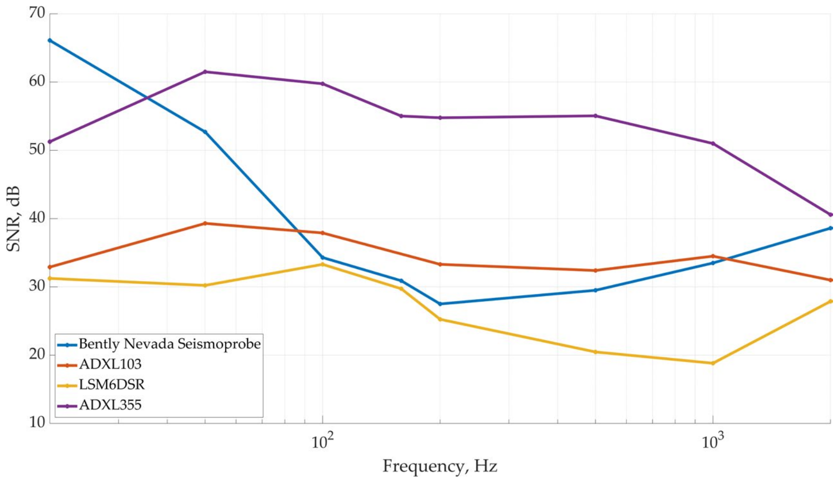

Figure 3. Comparison of SNR values as a function of signal frequency for all tested sensors.

ADXL103 and LSM6DSR are general-purpose MEMS accelerometers, suffering from nonlinearities in their sensing elements and signal conditioning circuits, leading to higher harmonic distortion. The ADXL355 has also the highest SNR values across all frequencies, indicating the best signal quality with minimal noise. This sensor is specifically designed for low-noise applications, featuring better internal ADCs and signal processing compared to the other MEMS sensors, which leads to its high SNR values. On the other hand, the Bently Nevada sensor exhibits a high SNR for low frequency vibrations but drops significantly as frequency increases. This may be due to the mechanical limitations of the velocity sensor, which may introduce more noise, leading to an SNR drop. Other possible reason could be signal attenuation at higher frequencies in velocity transducers. The ADXL103 and LSM6DSR have the lowest SNR values, staying mostly between 30–40 dB. These sensors likely have higher intrinsic noise due to their lower-cost MEMS fabrication and less effective internal noise filtering. Overall, the laboratory-grade Bently Nevada sensor performs well at lower frequencies but suffers from significant noise at higher frequencies.

The ADXL355 on the other hand is the best MEMS accelerometer in this comparison when it comes to signal quality, offering both low distortion (THD) and high SNR, making it ideal for precision vibration sensing. The ADXL103 and LSM6DSR show weaker performance, making them less suitable for high-fidelity measurements. However LSM6DSR could still be used for low-cost general purpose vibration monitoring.

4. Conclusions

This work presents the results of a study on the applicability of MEMS accelerometers for monitoring the dynamic state of rotating machinery. Selected MEMS sensors and an industrial sensor – Bently-Nevada Seimsoprobe – were subjected to a shaking test for various vibration frequencies that can occur during rotating machinery operation. The amplitude of vibration did not exceed the permissible vibration velocity values according to ISO 10816 (Mechanical vibration - evaluation of machine vibration by measurements on non-rotating parts). On the basis of the shaking tests, sensor signal quality characteristics have been gathered over the entire measurement band of the sensors. The characteristics include the relation between THD, SNR and SINAD and sine wave frequency. The test allowed to select the sensor with the best signal quality and compare it with an expensive commercial solution. Among the sensors evaluated, the digital MEMS sensor ADXL355 demonstrated signal quality comparable to that of the industrial-grade reference, indicating its viability as a lower-cost alternative in basic vibration monitoring applications. The LSM6DSR sensor is a first choice when price to performance ratio is critical. The analog MEMS sensor – ADXL103 was inferior in comparison to all sensors.

This study provides a fundamental assessment of MEMS accelerometers for vibration measurement under controlled laboratory conditions. While it does not address real-time or in-field diagnostics, it offers critical insights into sensor performance characteristics that are essential for developing cost-effective monitoring systems. The methodology and findings serve as a preliminary benchmark for selecting appropriate MEMS sensors based on signal quality requirements. The comparative approach used here can inform future studies focused on field deployment, sensor network integration, or long-term operational reliability. The results obtained highlight the system's capability to capture key vibration characteristics, paving the way for further advancements in data processing and analysis techniques. The ability to monitor dynamic vibrations with increasing accuracy and reliability is essential for preventing failures, optimizing performance, and ensuring safety in engineering systems. Future iterations of this research will focus on enhancing measurement precision, expanding the range of detectable frequencies, and integrating machine learning algorithms for intelligent fault detection. By addressing these challenges, this study serves as the first step toward a fully functional dynamic vibration monitoring system that can be deployed in a wide range of industrial and structural applications. The insights gained here not only validate the approach but also provide a strong foundation for future refinements and practical implementations.

Additional information

The authors declare: no competing financial interests and that all material taken from other sources (including their own published works) is clearly cited and that appropriate permits are obtained.

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