Capacitive MEMS accelerometer for condition monitoring

Alessandra Di Pietro, Giuseppe Rotondo, Alessandro Faulisi.
STMicroelectronics

1. Introduction

Predictive maintenance (PdM) is a key component of smart industry that involves monitoring equipment during operation to detect early the warning signs of potential failures. PdM is largely based on condition monitoring (CM) through the analysis of vibration, which is the most common method to detect imbalance, misalignment and other anomalies in machinery.
Traditional vibration sensing instruments are based on piezoelectric technology, but capacitive MEMS technology is gaining popularity in this field for various reasons involving flexibility and cost, and the fact that MEMS sensors are closing the gap to piezoelectric sensors in terms of bandwidth and dynamic range.
This paper describes the signal processing technique used during standard equipment operation to extract many of the parameters used for diagnosis and PdM, directly from an accelerometer integrated in a smart node. We also include a comparison between a triaxial digital ST capacitive MEMS sensor accelerometer (IIS2DH) and a conventional triaxial piezoelectric accelerometer.

2. Why use MEMS sensors instead of piezoelectric sensors?

Traditional vibration sensing instruments are based on piezoelectric technology, but capacitive MEMS technology is gaining popularity in this field for various reasons:

- fast recovery after high shock
- frequency response includes DC and is stable over time
- good stability over time and across temperatures
- digital output: easy wiring and no need for external ADC or other signal conditioning circuits
- integrated self-test
- embedded functionality
- low power, small size, low weight
- cost effective

STMicroelectronics has solutions required by the vast majority of vibration monitoring applications, with bandwidths over 5 kHz and superiority over piezoelectric sensors with respect to cost, ease of use, size and power consumption.

A highly compact smart sensor node with a MEMS accelerometer, a microcontroller, power management circuitry and wired or wireless connectivity offer the following advantages over the piezoelectric approach:

• embed cost effective sensor nodes inside machinery at strategic locations for vibration analysis
• deploy a distributed sensors architecture instead of a centralized one that requires more equipment
• continuously run vibration analysis during machine operation, and not according to maintenance schedules.

3. Signal processing for smart nodes with MEMS accelerometers

Signal processing in vibration analysis starts with a pre-filtering process applied to the accelerometer data and derived speed.

This data is then subject to time domain and frequency domain analyses.

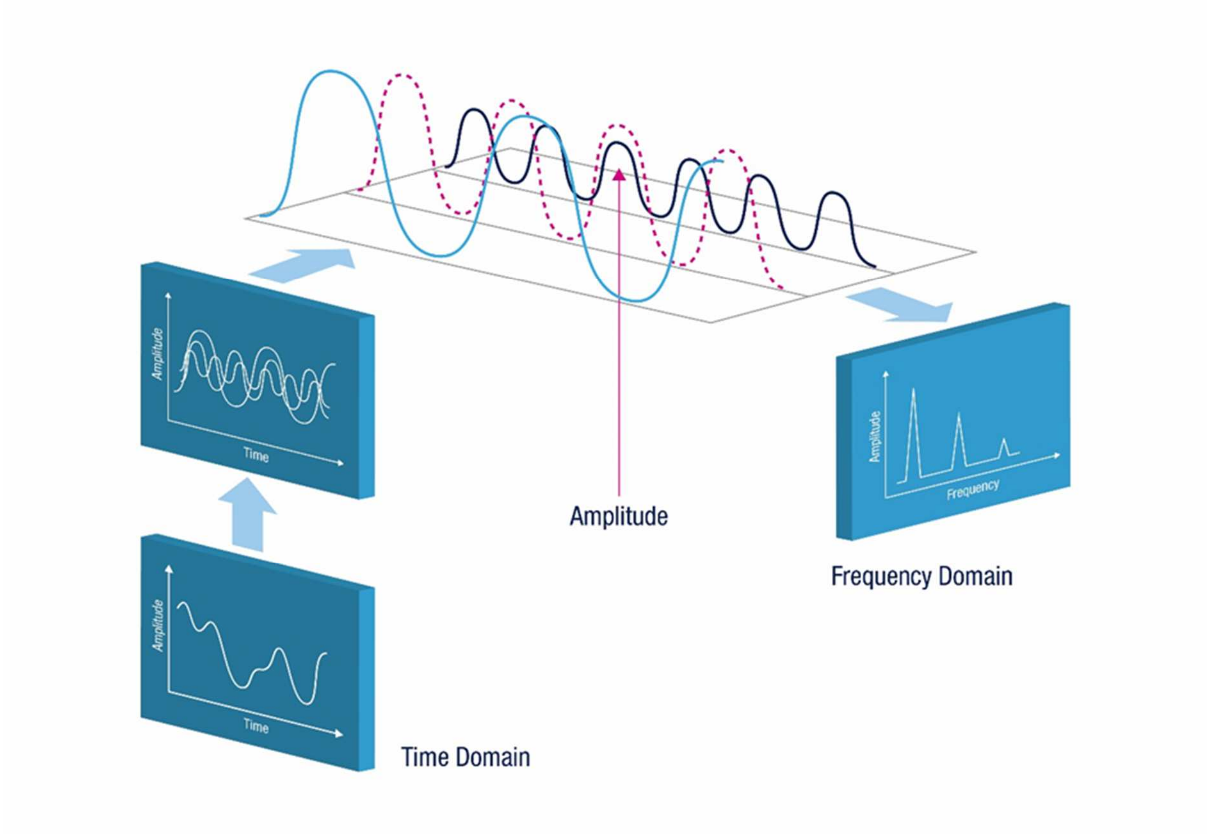

Figure 1: Generic vibration analysis from different perspectives speed

3.1 Pre-filtering block

The signal that carries acceleration data from the capacitive MEMS sensor contains a small DC bias that is compensated by a pre-filtering phase to render the acceleration and speed values suitable for vibration analysis in time and frequency domains.

3.1.1 High pass filtering of acceleration signals

For vibration measurements around a fixed point, the accelerometer usually provides a zero mean value. Therefore, in order to isolate the dynamic components of acceleration data, we use a high pass filter (HPF), to clear the static DC components from the signals.

3.1.2 Deriving speed data through mathematical integration

Once the static DC bias is filtered out, we can derive speed estimates from acceleration data through rectangular integration, which uses an accumulator to sum previous and current input samples and divide by the sampling rate. For more accuracy, we can implement trapezoidal integration, which acts as a first order hold on the system instead of the zero order hold of rectangular integration.
The numerical integration technique used in this application is the Newmark Method, which delivers acceptable results in a few simple iterations, as with the trapezoidal rule.

3.1.3 Speed filtering

Another problem that can interfere with the accuracy of our calculations is if the initial speed is not known to an acceptable degree of certainty; i.e., from direct measurement. If accurate initial speed data is not available, the results may inherit large linear drift errors because the signal will probably retain a small DC component after it has been integrated.
To avoid this high dependence on the initial conditions, we can insert another high pass filter block more after the numerical integration run for speed estimation.
The data conditioning chain is illustrated below.

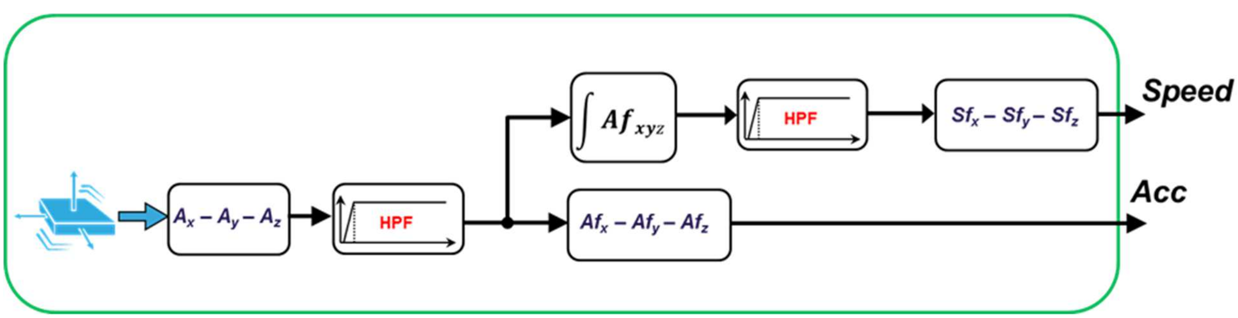

Figure 2: Pre-filtering block diagram

Where:

- Ax – Ay – Az = acceleration from three-axis MEMS accelerometer
- Afx – Afy – Afz = acceleration after high pass filtering
- Sfx – Sfy – Sfz = speed from numerical integration of acceleration data and additional high pass filtering

To summarize, the process involves the following three steps:

1. remove accelerometer DC components with a high pass filter offset
2. estimate speed through numerical integration of acceleration data
3. remove speed DC component with a high pass filter and so eliminate the need of an initial speed value.

3.2 Time domain analysis

The analysis of acceleration and speed data over time can provide overviews and trends regarding the operating performance of machinery. For instance, we can place capacitive MEMS sensors on motors to provide vibrational data along the radial (Axis1) and circumferential (Axis2) directions during normal operation.

The figures below show processed data from MEMS accelerometers placed on two different axes.

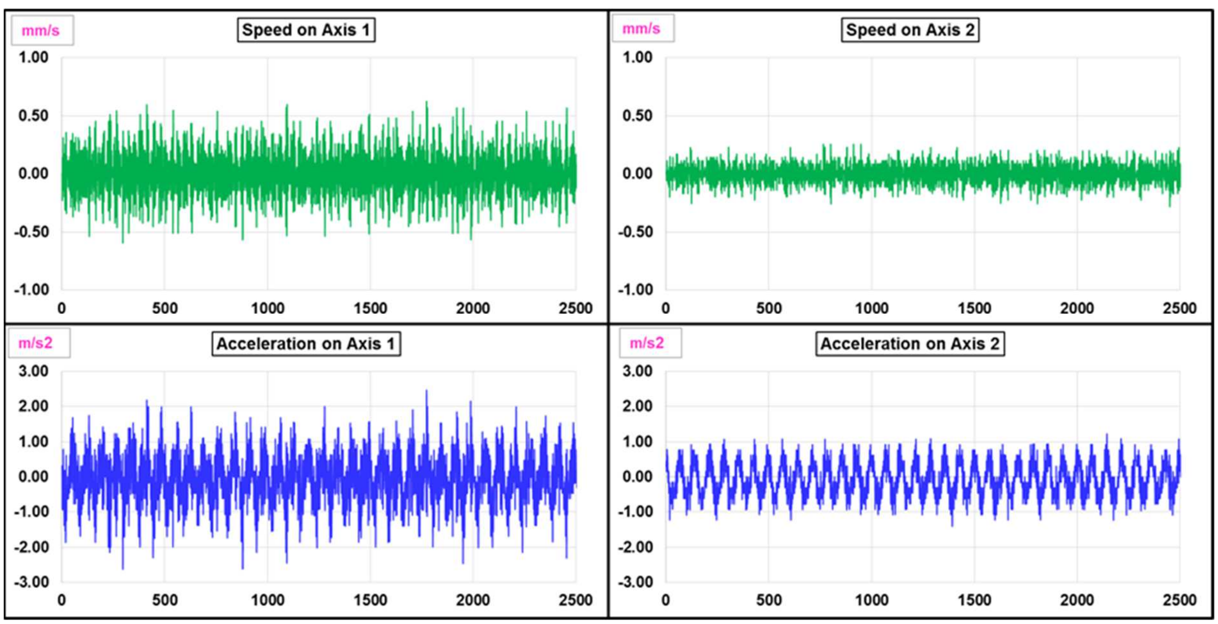

Figure 3: Generic speed and acceleration 2-axis data

Time domain data can be used to provide immediate parameter information for predictive purposes even before it is transformed into frequency domain data.
The Acceleration Max_Peak and RMS parameters can reveal spot and burst events, and indicate warning conditions as they approach threshold limits established by equipment manufacturers or introduced by the user.

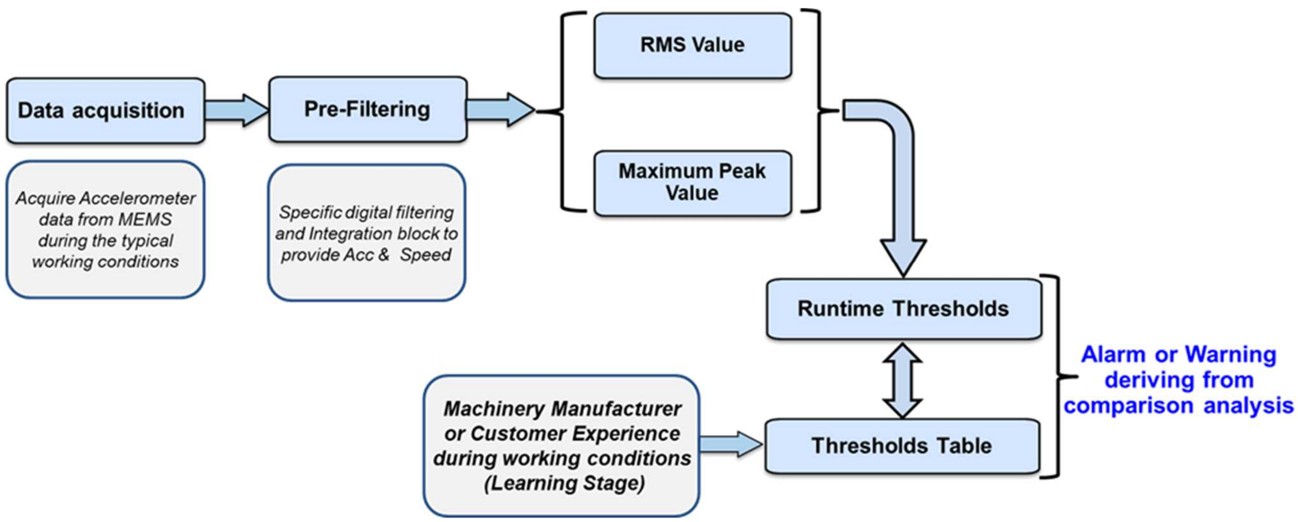

Figure 4: Time domain block diagram

3.3 Frequency domain analysis

To perform signal frequency analysis, vibration time domain data are discretized and gathered over a time interval and then broken down into component frequency waves through an optimized Discrete Fourier Transform (DFT) algorithm known as Fast Fourier Transform (FFT).

The parameters used in an FFT are listed below:

- N = discrete time domain samples
- fs = sampling frequency
- fmax = fs/2 = maximum frequency spectrum
- fs/N = frequency resolution; space between frequency lines (bins)

To obtain reliable frequency domain data, certain data sampling techniques based on windowing must first be applied

3.3.1 Windowing of sample waveforms

FFT is applied successfully to a periodic signal and when an integer number of periods is contained in the acquisition time (Fig.5). Since the FFT is applied to a truncated signal, the risk is that the number of signal periods is not an integer and the acquired signal endpoints are discontinuous (Fig.6); these discontinuities introduce high frequency and the FFT is not the right spectrum of the original signal, but a spread version.

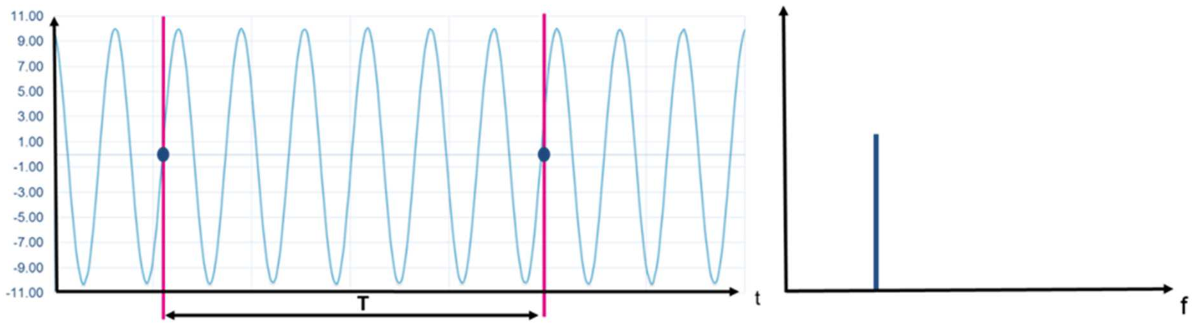

Figure 5: Signal acquisition and related spectrum with a whole number of periods

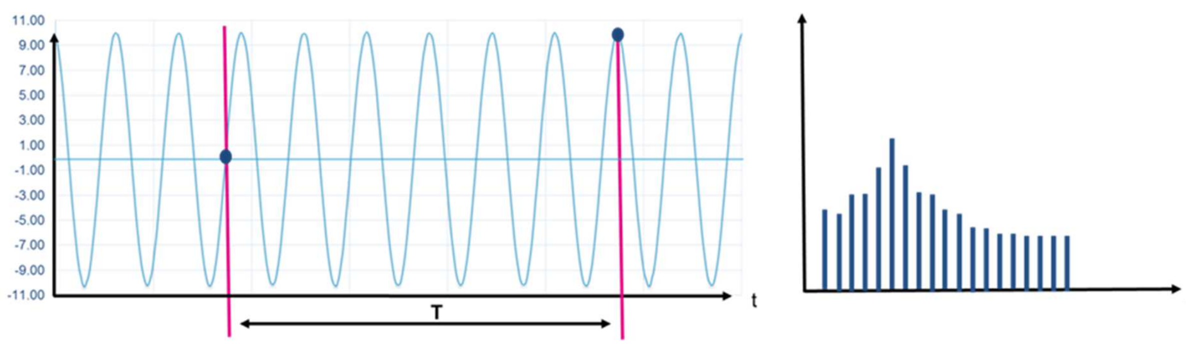

Figure 6: Signal acquisition and related spectrum without a whole number of periods

To avoid this, a window function is multiplied to the acquired time domain data set before the FFT.
The correct window function to apply depends on a trade-off between the width of the main lobe, side lobe attenuation, process loss and spectral leakage.
The Hanning window represents a good solution for composite signals typical of rotating equipment.

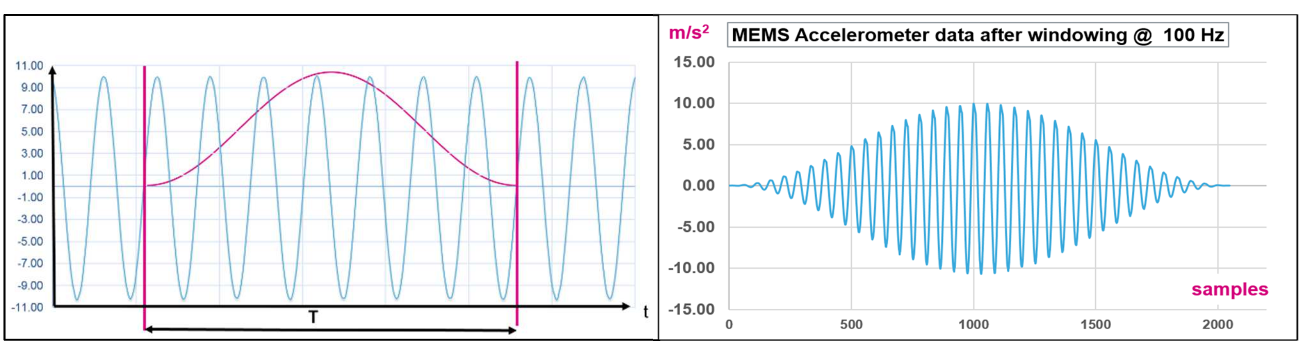

Figure 7: Time domain signal before and after Hanning windowing process

3.3.1.1 Averaging to remove noise

Signal processing techniques that address spectral leakage do not address probable noise, and increasing the FFT size only improves frequency resolution (reducing the width of frequency bins).

The usual solution for noise is averaging several spectra across multiple FFT records, with the average amplitude value computed for each harmonic component.

3.3.1.2 Overlapping

FFT is based on the assumption that a signal is stationary; otherwise, the FFT may miss certain events. The overlapping technique divides long signals into smaller data blocks and overlaps them.

In the windowing process, the acquired data samples in each data block are amplified or attenuated according to their position.

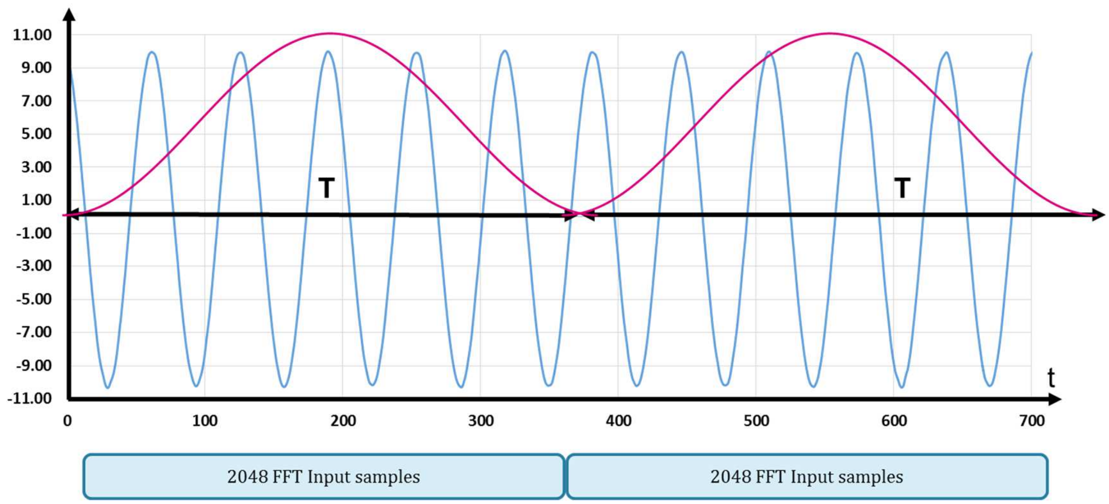

Figure 8: Data block acquisition with 0% overlapping

Following the overlapping technique, the result of the several FFTs can be averaged to reduce noise.

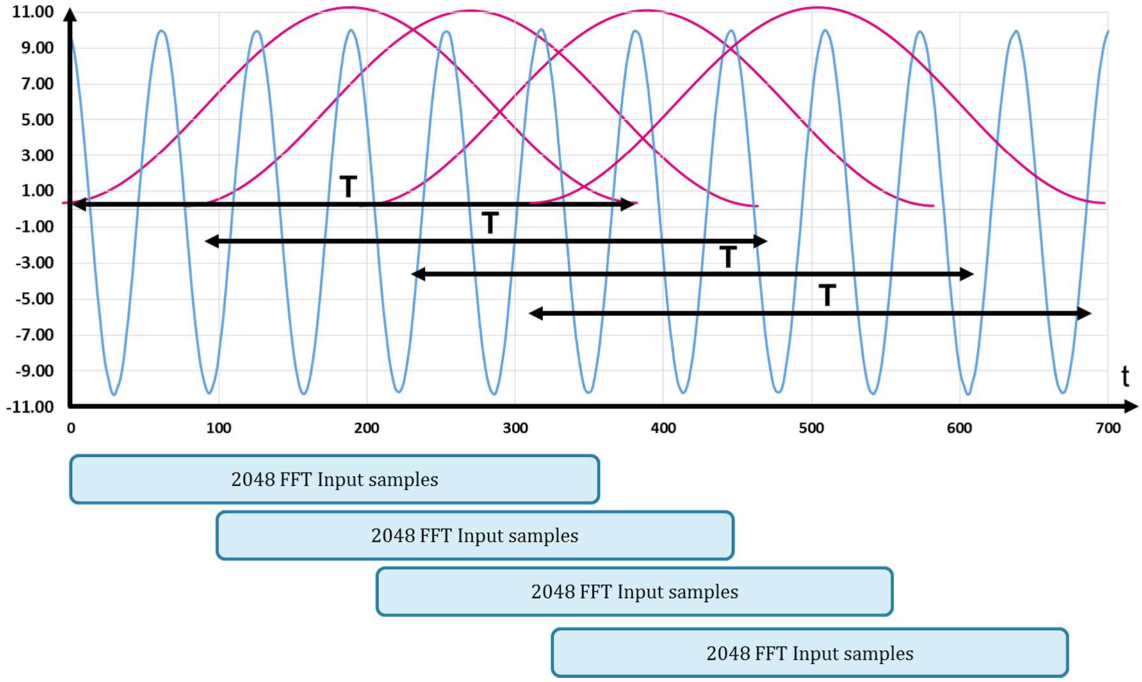

Figure 9: Data block acquisition with 0% overlapping

The following figure shows the averaging process for five FFTs on time domain data blocks with 0% overlapping and with 75% overlapping; the latter implemented over decidedly less time.

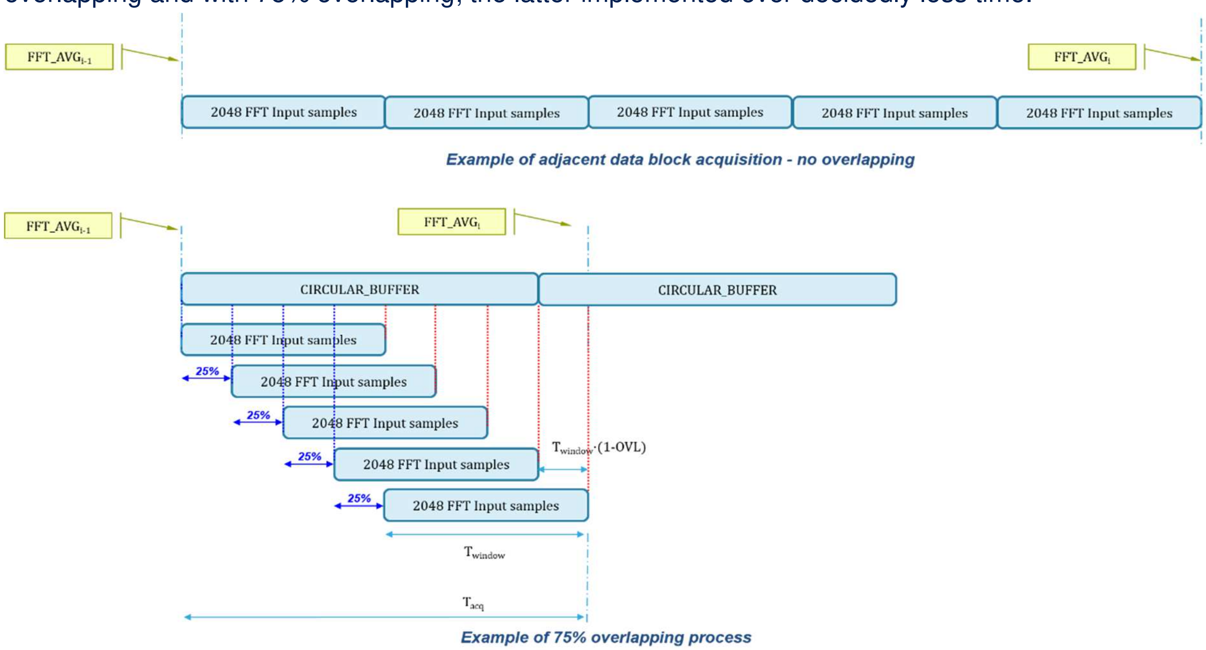

Figure 10: Data block acquisition without overlapping and with 75% overlapping

3.3.2 Using the STM32 microcontroller for advanced signal processing

A smart node based on a capacitive MEMS accelerometer and a suitable MCU can integrate advanced time and frequency domain processing: the capacitive MEMS accelerometer provides digital data to the microcontroller, which performs filtering, windowing, and FFT averaging of acceleration and speed frequency spectra, as shown in the following figure.

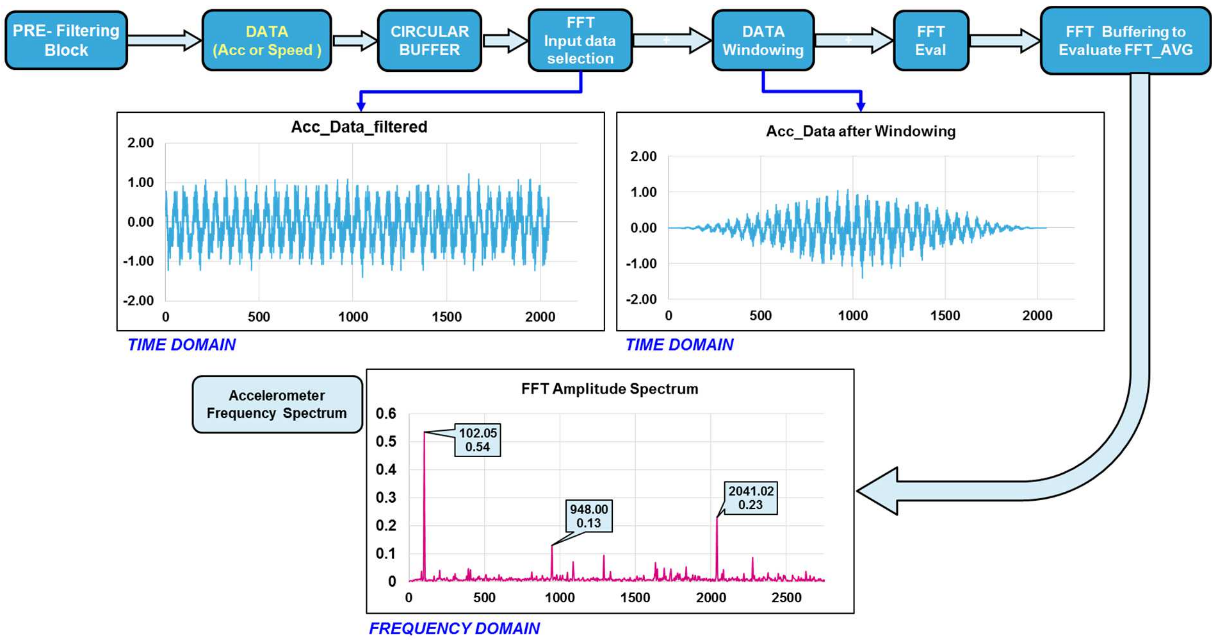

Figure 11: Full path from accelerometer data to frequency domain block diagram

The STM32 ARM® Cortex®-M4 32-bit microcontroller with FPU and loaded CMSIS DSP_Lib is very well suited to real-time processing such as filtering and FFT.
The important CMIS DSP_Lib functions for this application are:

- arm_mult_f32 (for windowing)
- arm_rfft_fast_f32 and arm_cmplx_mag_f32 (for FFT evaluation)
- arm_max_f32 (to evaluate the max FFT peak and frequency)

In our example, 3-axis digital MEMS accelerometer data are acquired by the microcontroller at the 5.3 kHz output data rate of the sensor via the SPI communication interface, which is best suited for such high data rates.

To ensure real-time performance, with no accelerometer data loss during processing, a dual buffer approach can be used with a circular buffer to collect sampled accelerometer data and a secondary buffer to hold only the data block to be subjected to FFT or some other analysis.

When the circular buffer is filled with the first data block to process, it is transferred to the secondary buffer and processed in parallel, while the circular buffer continues to collect data block samples. The dual buffer strategy also provides advantages for implementing FFT averaging.

A UART or USB peripheral can transfer results to a PC for further analysis. A direct memory access (DMA) controller is used to manage data transmission in the background, without the intervention of the Cortex-M4 processor. During this operation, the main processor can execute other tasks and it is only interrupted when a whole data block is available for processing.

3.3.3 Performance

The following table shows the execution time of some main functions implemented on the STM32F469AI using IAR Embedded Workbench for ARM (EWARM) toolchain Version 7.80.2 with no optimization.

	MCU: FPU, clock @180 MHz	**Execution time (µs)**					
	Functions	**Buffer FFT Input Size**			**Total Execution Time**		
		512	**1024**	**2048**			
Time Domain Processing	HPFiltering on Accelerometer (3D)	1	1	1	**14.6**		
	Storage in Circular Buffer (3D)	0.6	0.6	0.6			
	Accelerometer Max Peak (3D)	1	1	1			
	Accelerometer Integration (3D)	11	11	11			
	HPFiltering on Speed (3D)	1	1	1			
Frequency Domain Processing	FFT Input Buffering from Circular Buffer (1D)	10.5	19.7	38.5	**350.5**	**691.3**	**1498**
	Input Buffer Filtering with Hanning Window: • arm_mult_f32 (1D)	20.7	40.6	80.4			
	FFT processing: • arm_rfft_fast_f32 (1D)	217	427	972			
	• arm_cmplx_mag_f32 (1D)	90	180	360			
	• arm_max_f32 (1D)	12.3	24	47.5			

Table 1: Execution time of main signal processing functions on STM32F469AI

3.3.4 Analysis based on threshold comparison

One of the key advantages of frequency domain analysis using the FFT method is the ability to identify the root cause of a problem by examining the frequencies and the related amplitudes of the frequency spectrum.

The frequency spectrum represents the signature of rotating equipment. For example, a high vibration amplitude on the rotation speed is most probably due to motor imbalance, while bearing degradation and gear mesh faults exhibit vibrations at specific high frequencies that are a function of equipment geometry.

The figure below compares the frequency spectrum when the motor is in good working condition and when the same motor is not balanced.

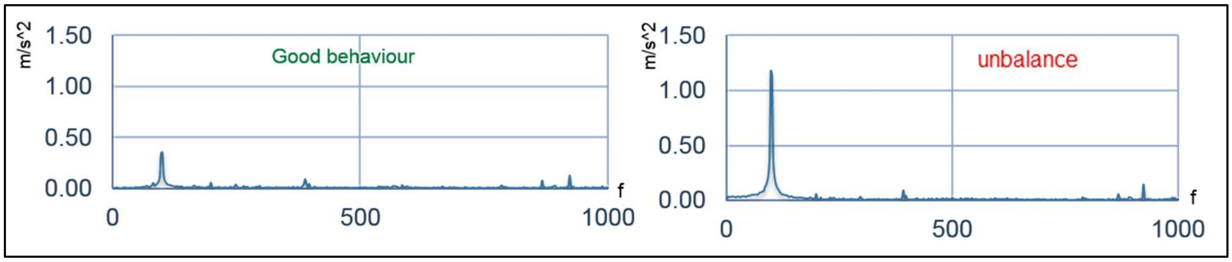

Figure 12: Spectrum of equipment rotating at 6000 RPM (100Hz) in normal condition and with imbalance

Manufacturers can therefore provide threshold values for motor signatures to identify warning and critical levels related to specific subrange levels in machine vibration.
Figure 13 shows an example that highlights the following conditions:

- the 1st natural frequency in the machine (**Normal**)
- the 3rd and 6th harmonics (**Critical**)
- two other frequencies (**Warning**)

A microcontroller can then compare warning and alarm thresholds with frequency domain data from working equipment. The warning levels are particularly important for predictive maintenance as they can indicate trends that require attention before they cause a fault.

In time domain analyses, thresholds can also be compared with peak, peak to peak and RMS data for speed and acceleration to monitor the status and trends of working equipment.

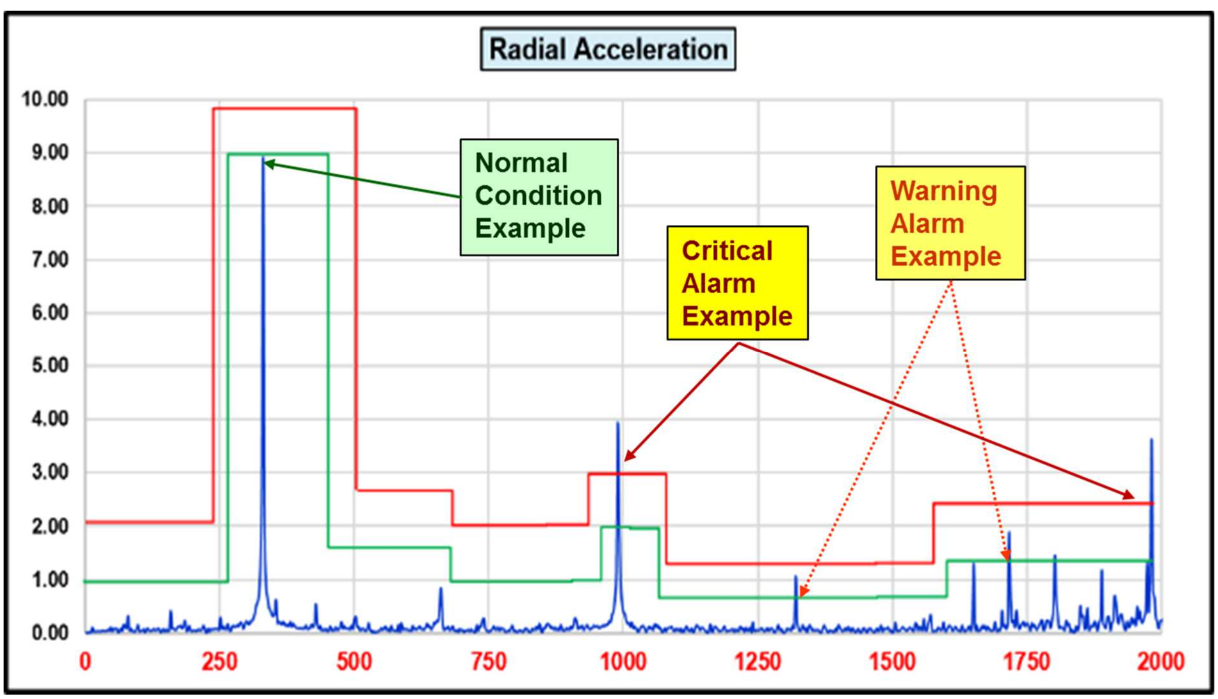

Figure 13: Spectral band thresholds for warning and alarm conditions

4 Comparison of capacitive MEMS and piezoelectric accelerometer technologies in vibration monitoring

This section compares vibration monitoring in time and frequency domains for capacitive MEMS and piezoelectric accelerometer data in the 2 kHz frequency range.

4.1 Test setup

The test in fig15 consists of a shaker, a PC for data collection and storage, a triaxial piezoelectric accelerometer and a sensor node.
The smart sensor node integrates an IIS2DH digital triaxial capacitive MEMS accelerometer from STMicroelectronics with an ARM® Cortex®-M4 32-bit microcontroller and suitable power management circuitry as schematized in the following block diagram.

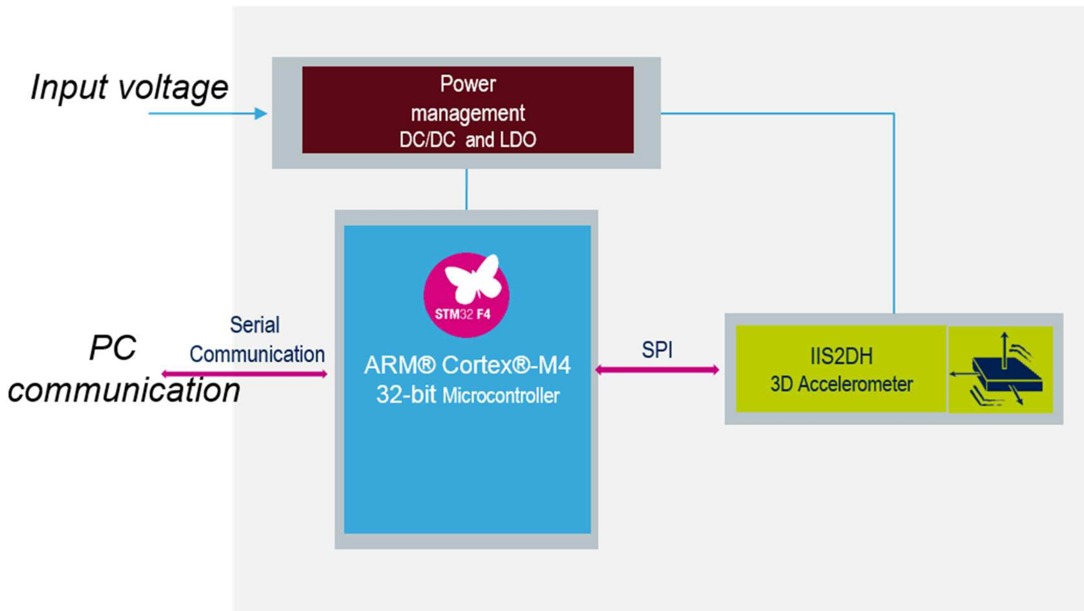

Figure 14: Sensor node block diagram

The piezoelectric accelerometer sensor and smart node are placed very close to each other and are glued to a metal base screwed to the shaker.

The flow of data for each accelerometer is listed below:

- MEMS accelerometer: raw data are sent via SPI to the microcontroller, which performs signal processing and sends results to PC via USB.
- piezoelectric accelerometer: analog data are digitalized and sent to a PC for signal processing in Matlab.

The signal processing employed for both sensors are the same and based on Hanning windowing and 2048-point FFT.

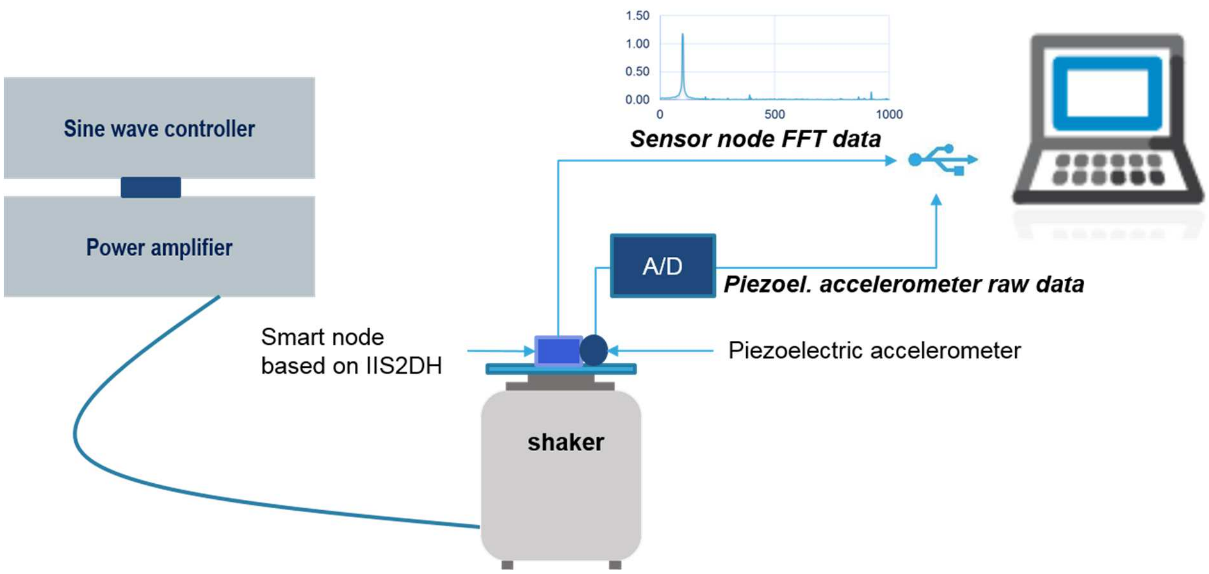

Figure 15: Test setup

4.2 Test description and results

The sinusoidal signals were applied to the shaker at three different frequencies and at the same amplitudes of 10 m/s²:

- Frequency_1: 100 Hz
- Frequency_2: 500 Hz
- Frequency_3: 1000 Hz

The raw data of the two accelerometers were collected in the same test session with the following sampling frequencies:

- 5.3 kHz for the IIS2DH MEMS accelerometer
- 6.4 kHz for the piezoelectric sensor

The figures below show the acquired sensor data in the time domain (before and after windowing), and the frequency domain spectrum at the 3 different sinusoidal excitations.

4.2.1 Sinusoidal shaker excitation at 100 Hz

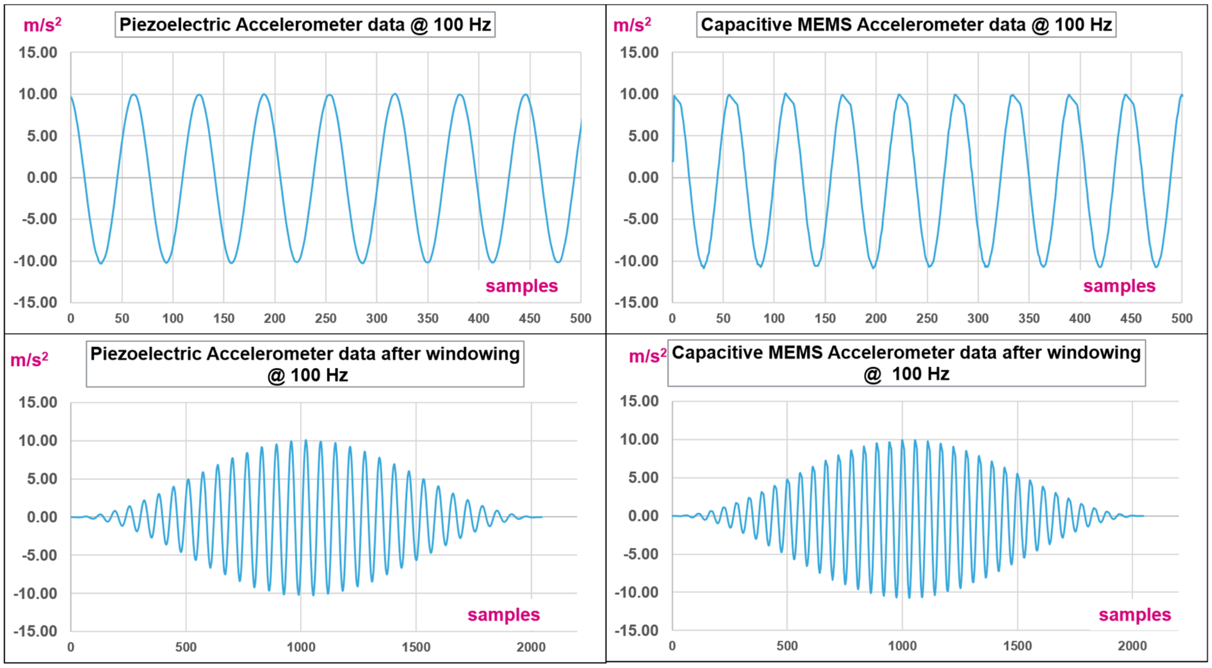

Figure 16: Piezoelectric and capacitive MEMS time domain data comparison with shaker at 100 Hz

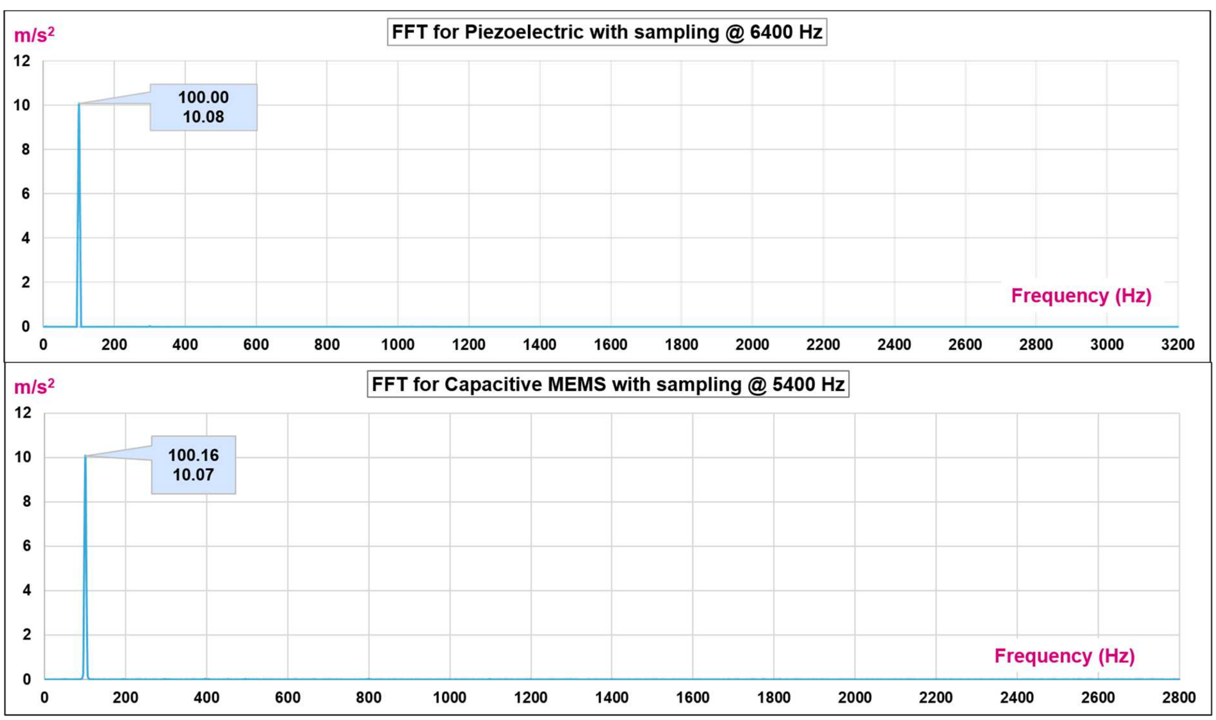

Figure 17: Piezoelectric and capacitive MEMS frequency domain data comparison with shaker at 100 Hz

4.2.2 Sinusoidal shaker excitation at 500 Hz

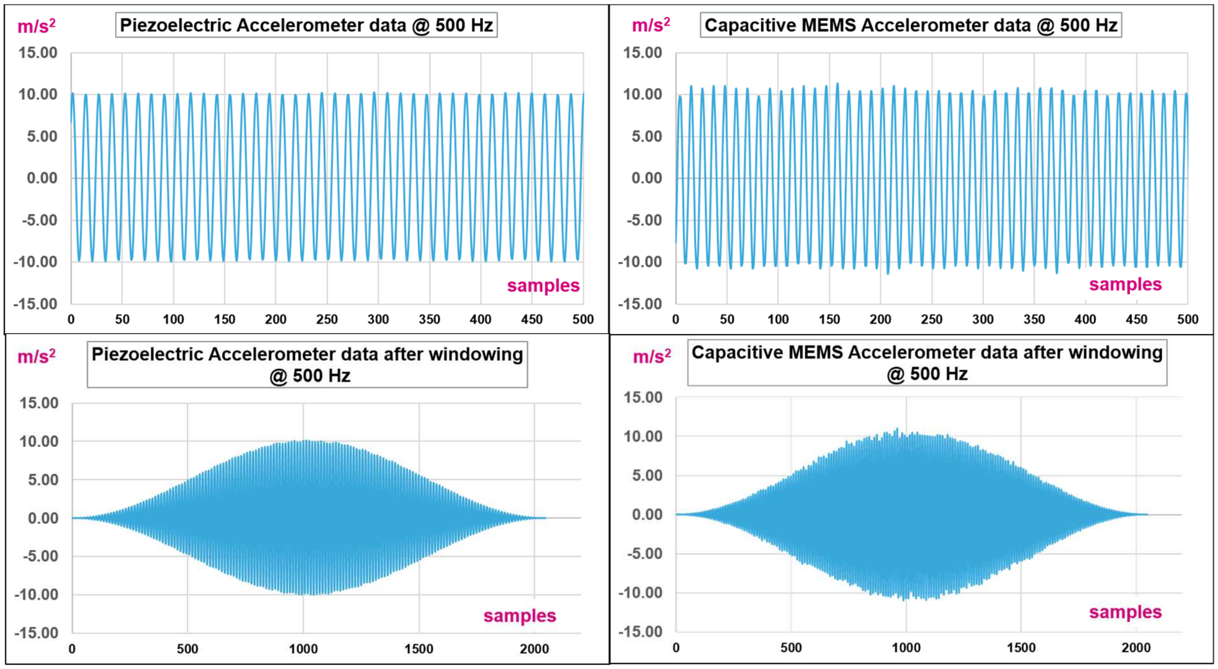

Figure 18: Piezoelectric and capacitive MEMS Time domain data comparison with shaker at 500 Hz

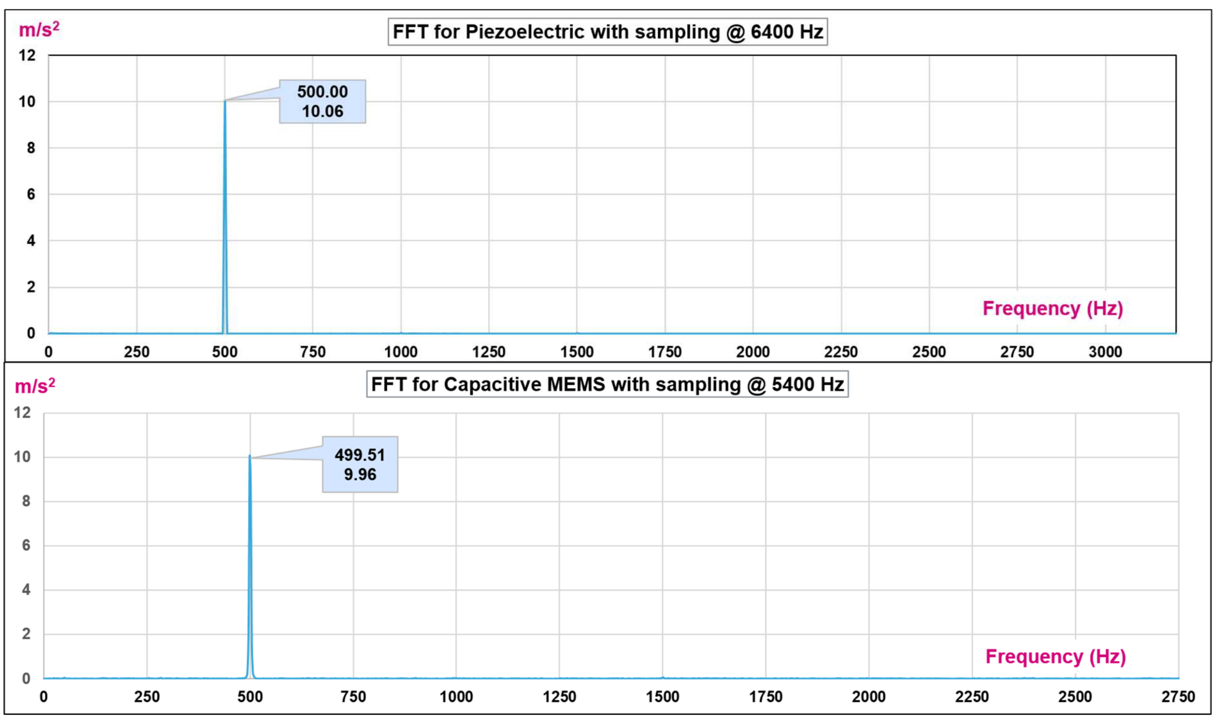

Figure 19: Piezoelectric and capacitive MEMS frequency domain data comparison with shaker at 500 Hz

4.2.3 Sinusoidal shaker excitation at 1 kHz

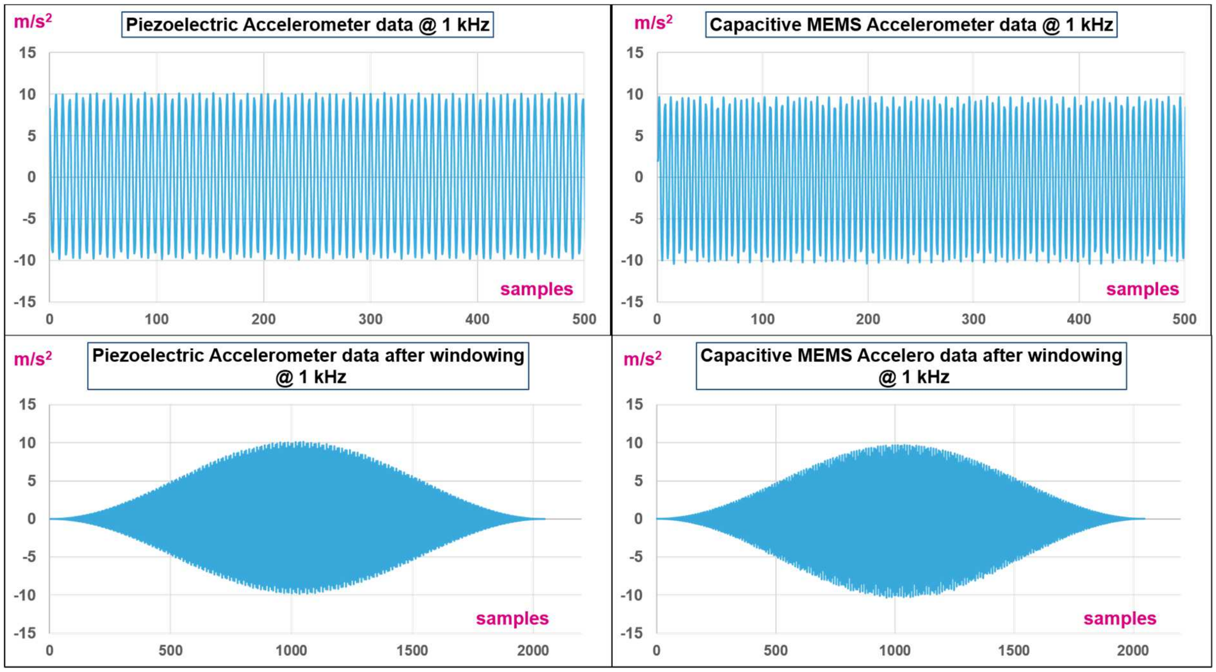

Figure 20: Piezoelectric and capacitive MEMS time domain data comparison with shaker at 1 kHz

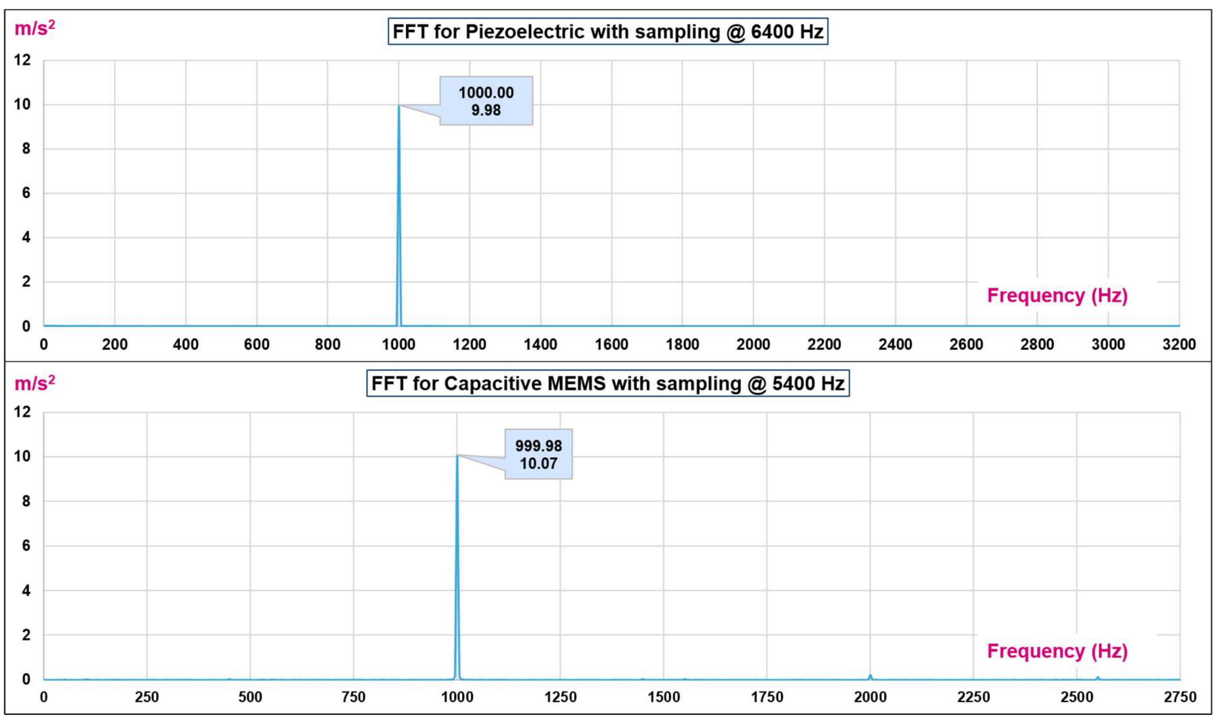

Figure 21: Piezoelectric and capacitive MEMS frequency domain data comparison with shaker at 1 kHz

The above plots show the measurements taken by the capacitive MEMS and piezoelectric accelerometer are highly accurate for each set frequency, as well as for the amplitudes.

This demonstrates that the IIS2DH triaxial digital MEMS accelerometer achieves a performance level that is suitable for condition monitoring of machines with characteristic frequencies up to 2 kHz.

5 Conclusion

Capacitive MEMS sensors with suitable microcontrollers can perform advanced signal processing for time and frequency domain vibration analysis for predictive maintenance. Their small form factor and low power consumption allow easy integration in standalone smart nodes that can even be battery operated, and which may be retrofit in current machinery and equipment.

The IIS2DH with 2 kHz flat frequency band provides a frequency response that is suitable for many machine health applications.

Further use cases for defects and wear detection can use the same techniques herein with new generation accelerometers from STMicroelectronics with higher bandwidths, lower noise and optimized frequency responses. Emerging ST technologies also promise analog capacitive MEMS microphones as viable alternatives to piezoelectric sensors in higher spectral bands from audio to ultrasound frequencies.