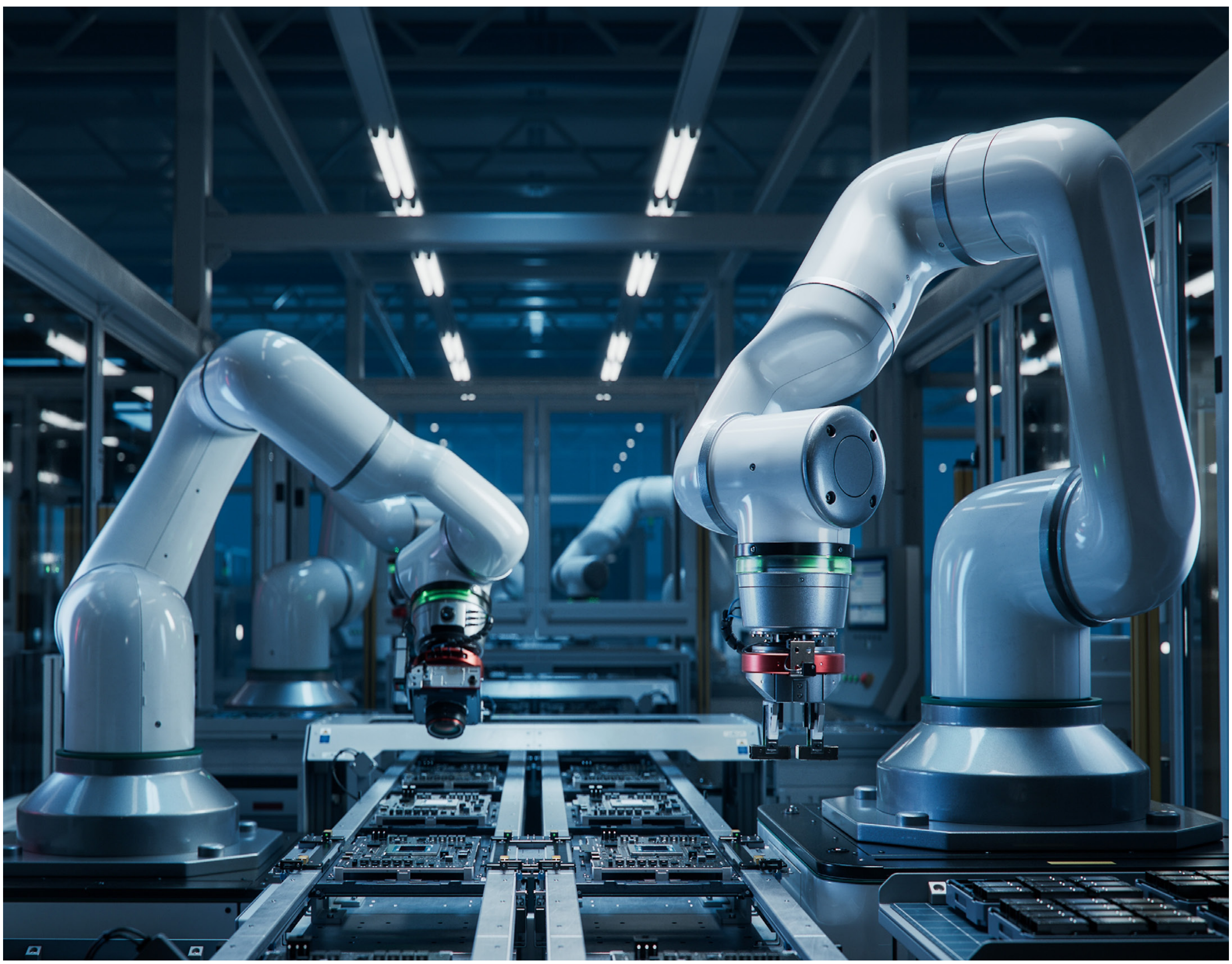
PREDICTIVE HARMONY: ENHANCING MAINTENANCE THROUGH VIBRATION SENSOR TECHNOLOGY



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INTRODUCTION:

With the continuous advancement of technology in industrial applications, there is an ongoing need to update best practices in order to optimize productivity, efficiency, and cost savings. Condition-based monitoring (CBM) serves as a means to accomplish these goals effectively.

CBM is a maintenance strategy that involves monitoring equipment to predict when maintenance is necessary. This approach is more cost-effective than traditional preventative maintenance, which involves regularly scheduled maintenance regardless of equipment condition. CBM allows maintenance to be performed only when necessary, reducing downtime and saving costs.

With the advent of the Internet of Things (IoT), CBM has become more accessible and economical. IoT-based CBM uses wireless sensors to monitor equipment conditions in real-time. Advances in edge processing and artificial intelligence (AI) technology make it possible to analyze sensor data in real-time, enabling early detection of equipment faults and enhancing predictive maintenance.

Various sensors are utilized in CBM to assess the health of machinery and equipment. These sensors include vibration sensors for detecting mechanical vibrations, pressure sensors for monitoring gas or liquid pressure, temperature sensors for measuring thermal conditions, current sensors for evaluating electrical current flow, and oil analysis sensors for analyzing lubricating oil properties. In this whitepaper, we will discuss the characteristics of IoT-based predictive maintenance systems and explore the use of vibration sensors for CBM in depth.

WIRELESS COMMUNICATION PROTOCOLS

Selection of the wireless communication protocol is an important aspect when designing an IoT-based CBM system. These protocols enable data to be transmitted wirelessly from sensors to a central monitoring system. There are several wireless communication protocols available, each with advantages and limitations. In this whitepaper, we will discuss three common protocols: Bluetooth Low Energy (BLE), LoRaWAN, and NB-IoT.

BLUETOOTH LOW ENERGY (BLE):

BLE is a wireless communication protocol commonly used in IoT-based CBM systems. BLE operates in the 2.4GHz frequency band and has a range of up to 100 meters. BLE is designed to be energy-efficient, making it an ideal choice for battery-powered sensors. BLE is also supported by most modern smartphones, making it easy to configure and monitor sensors remotely.

One limitation of BLE is its short range, which may not be sufficient for large industrial facilities. Additionally, BLE may experience interference from other wireless devices operating in the same frequency band, leading to potential data loss or delays.

LoRaWAN:

LoRaWAN (Long Range Wide Area Network), or LoRa, is a low-power, wide-area networking (LPWAN) wireless communication protocol that operates in the sub-gigahertz frequency range. LoRa has a range of up to 10 kilometers in rural areas and up to 2 kilometers in urban areas. LoRa is designed to be energy-efficient, making it an ideal choice for battery-powered sensors.

LoRa is well-suited for IoT-based CBM systems because it can penetrate walls and other obstacles, making it suitable for large industrial facilities. However, LoRa's low data rates may not be sufficient for applications that require real-time monitoring and control. This problem can be mitigated with the use of edge computing, so that decisions can be made locally, and only important information is transmitted to the host system.

LTE, NB-IoT AND LTE-M:

LTE (Long-Term Evolution) is a high-speed wireless communication technology commonly used for mobile networks, designed to handle high bandwidth applications. NB-IoT (Narrowband IoT) and LTE-M are both LPWAN (Low Power Wide Area Network) technologies within the LTE framework, designed specifically for IoT applications. These technologies provide low-power, long-range connectivity with excellent penetration through obstacles.

NB-IoT provides long-range, low-power connectivity optimized for applications with low data rates, while LTE-M offers a balance between data rates and power consumption, making it suitable for a broader range of IoT applications including mobile assets.

NB-IoT is a cellular wireless communication protocol optimized for low-power IoT applications with low data rates. It operates within the LTE framework and utilizes the existing LTE infrastructure for connectivity, providing reliable connectivity and security. NB-IoT has a range of up to 10 kilometers and can support a large number of devices. One limitation of NB-IoT is its dependence on cellular networks, which may not be available in remote areas.

LTE-M, also known as LTE Cat M1 or eMTC (enhanced Machine Type Communication), is another LPWAN technology within the LTE framework. It supports voice, data, and mobility services with improved coverage compared to traditional LTE. LTE-M offers a balance between data rates and power consumption, making it suitable for a wide range of IoT applications such as asset tracking, wearables, and smart utilities. LTE-M consumes more power compared to other LPWAN technologies like NB-IoT, and is reliant on the availability of a regional network infrastructure.

OTHER:

Several other protocols including Wi-Fi, Zigbee, Cellular (3G, 4G, 5G), and WirelessHART are used in CBM applications. Wi-Fi provides high-speed data transfer and seamless integration with existing network systems. Zigbee is suitable for creating wireless sensor networks with low power consumption and efficient bandwidth usage. Cellular communication offers wide-area coverage and reliable connectivity, making it ideal for remote or geographically dispersed deployments. WirelessHART is designed specifically for industrial environments, enabling integration with existing HART systems. Satellite communication is another wireless option used in CBM, particularly in remote or inaccessible areas.

Ultimately, the choice of wireless communication protocol in CBM depends on factors like range, power consumption, data transfer speed, latency, infrastructure availability, and cost. Each unique application will require consideration of these factors to determine which is the best option.

HAZARDOUS LOCATION CERTIFICATION

Another element related to CBM to consider is hazardous location certifications. Hazardous location certification is used to ensure the safety of electrical and electronic equipment used in potentially hazardous environments, such as those where flammable gases, vapors, liquids, dusts, or fibers may be present. These environments can include chemical plants, refineries, oil and gas production facilities, grain elevators, and other similar industrial facilities where CBM may be employed.

Hazardous location certification is typically performed in accordance with a set of standards that provide a framework for testing and certifying electrical and electronic equipment for use in hazardous locations, based on the specific hazards that may be present in the environment.

Standards have been developed by various organizations, such as the National Electrical Code (NEC) in the United States, the Canadian Electrical Code (CEC) in Canada or the International Electrotechnical Commission (IEC). ATEX (ATmosphères EXplosibles) is a set of European Union directives that are similar in nature to the NEC and CEC standards. IECEx is a globally recognized hazardous location certification system based on IEC standards.

There are many different types of hazardous location certifications, including Class, Division, and Zone certifications. These certifications are used to indicate the level of safety provided by the equipment in a particular environment.

Class certifications refer to the type of hazard that is present, such as flammable gases or dusts. Division certifications indicate the likelihood of the hazard being present, such as continuous or intermittent exposure. Zone certifications are used to indicate the level of protection provided by the equipment.

MEMS AND PIEZO TECHNOLOGY

After considering the wireless communication protocols and possible hazardous location certifications that may affect some CBM practices, exploring the vibration sensors that enable CBM is crucial. Two types of vibration sensors commonly used in CBM are MEMS and Piezo Accelerometers. Variable Capacitance (VC) MEMS sensors are based on micro-electromechanical systems (MEMS) technology and are typically used for slow rotating equipment, such as conveyor belts, compressors, and wind turbines.

Piezo accelerometers, on the other hand, are ideal for high-frequency measurement, making them well-suited for early fault detection. These sensors use piezoelectric materials that generate an electrical charge in response to mechanical stress. They can detect high-frequency vibrations that may indicate early signs of equipment failure. This is typically used to predict faults in gearboxes, high speed turbines and pump cavitation.

VC MEMS

VC MEMS sensors work by measuring changes in capacitance caused by changes in the relative position of interdigital electrodes. These changes are converted into an electrical signal, which is then processed and analyzed.

In a capacitive MEMS accelerometer, the inertial movement of one array of fingers relative to a fixed array is sensed by measuring change in capacitance between the arrays. This is usually done by allowing the change in capacitance to modify a frequency, well above the intended detection bandwidth, which can then be demodulated to obtain a final analog output. Since the device is constantly excited, the power consumption is traditionally significantly higher than that of a piezoelectric device. However, newer devices have wake up functions and improvements in electronics that help significantly reduce power consumption. Until relatively recently, capacitive MEMS devices have been limited to low-frequency operation, although there is a trend towards higher-bandwidth devices as technology improves.

VC MEMS sensors are commonly used in IoT-based CBM systems to monitor slow-rotating assets such as conveyor belts. These sensors can detect low-frequency vibrations, making them ideal for detecting changes in vibration patterns that may indicate misalignment, belt wear, or other issues. For example, in a mining operation, VC MEMS sensors can be used to monitor the conveyor belts that transport minerals from the mines to the processing plant. Additionally, VC MEMS sensors are small, lightweight, and energy-efficient, making them ideal for battery-powered sensors.

Due to their relatively low frequency response VC MEMS sensors may not be suitable for high-speed rotating equipment, where other types of sensors such as piezo accelerometers may be more appropriate.

PIEZO TECHNOLOGY

Piezoelectric sensor technology is commonly used in CBM systems to measure high-frequency vibrations enabling early detection of faults in rapidly rotating equipment. These sensors use piezoelectric materials that generate an electrical charge in response to mechanical stress. Piezo sensors work by converting mechanical vibrations into an electrical charge, which is then measured and analyzed. Piezo sensors can detect vibrations in the high-frequency range, typically up to 20 kHz, providing valuable information about the condition of the equipment.

For example, in a wind turbine, piezo accelerometers can be used to monitor the gearbox for early signs of damage. By monitoring high-frequency vibrations, it is possible to detect changes in the vibration pattern that may indicate bearing wear, gear tooth damage or other fault conditions. Early detection of defects can help prevent catastrophic failure and reduce downtime.

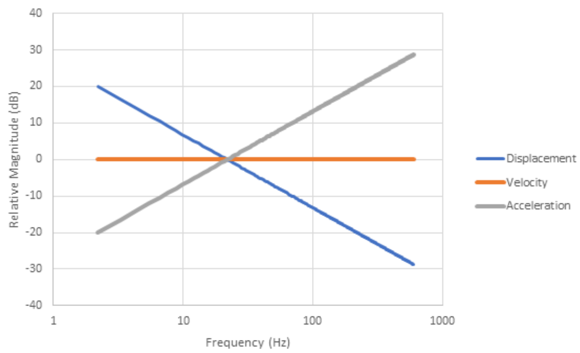
In a piezo-electric accelerometer the sensing element is typically a piezoelectric ceramic material (or "crystal") loaded in shear by an inertial mass. Due to the high stiffness and high charge sensitivity of the crystal and the relatively low mass required to achieve typical detection ranges for condition monitoring, the resonance frequency will be minimum >30 kHz, with some designs >50kHz. This allows the passband to extend well beyond 10 kHz. The piezoelectric sensing element itself requires no power, and signal conditioning can be provided within a device with very low current requirement. Piezoelectric accelerometers can achieve very high bandwidth and superior noise performance (signal resolution).

One of the advantages of piezo sensors is their ability to detect early faults in rotating equipment, such as bearing defects or unbalance. Additionally, piezo sensors are small, lightweight, and energy-efficient, making them ideal for battery-powered sensors. However, piezo sensors may not be suitable for low-frequency vibrations, which may require other types of sensors such as VC MEMS sensors discussed above.

VELOCITY, ACCELERATION AND DISPLACEMENT

For frequencies up to 1 kHz it may be useful to examine vibration data presented in velocity units because in very general terms, machine vibration will demonstrate the following:

- Displacement tends to be high at low frequencies, and falls with increasing frequency
- Acceleration tends to be low at low frequencies, and rises with increasing frequency
- Velocity tends to be relatively constant over frequency



Note that X and Y axes are both logarithmic scaling in this plot.

The measured velocity of a real system tends to be relatively constant over frequency but may not be perfectly flat.

The relationship between the displacement, velocity, and acceleration spectra is fixed since velocity is the first derivative of displacement with respect to time, and acceleration is the second derivative.

Since velocity is relatively constant over frequency, it is possible to define a single threshold that will apply whether the machine is running at 100 rpm or 1000 rpm. Various standards exist that define acceptable limits for machine vibration in terms of velocity measurements (for example, ISO 20816 series).

VIBRATION SIGNAL ANALYSIS

TIME DOMAIN DATA

Time domain refers to the representation of signals in terms of changes over time, showing how the signal amplitude varies during a certain period. Vibration signal analysis for machine condition monitoring usually starts with the acquisition of a block of time-domain data at a fixed sampling rate.

Analysis in the time domain produces useful information: The RMS (square root of the mean of the squared sample values) yields the total signal power, and this provides an indication of the overall vibration level present. In vibration analysis, the presence of a static acceleration (such as gravity) is not generally of interest, and vibration measurements are therefore normally "AC-coupled".

Other characteristics of the time signal that may be of interest for condition monitoring include the maximum peak-to-peak value within the acquired time block, the crest factor (peak amplitude divided by RMS level), and kurtosis (a good indicator of the "spikiness" of the data).

FREQUENCY DOMAIN DATA

For more detailed analysis, it is useful to inspect the frequency content of the signal. Frequency domain refers to the representation of signals in terms of their frequency components. This shows the frequency components present in the signal and the strength or energy of each. In the frequency domain, we can identify the presence of specific frequencies that may be associated with certain faults in the machine.

Blocks of time-domain data can be converted into the frequency domain (magnitude v frequency) using the Discrete Fourier Transform (DFT), and most commonly using a variant of DFT known as the Fast Fourier Transform (FFT) which offers significantly more efficient processing when the time signal block length has an integer power of 2 samples (such as 1024, 2048, 4096, etc).

The FFT output is a complex-valued array of N values, where N is the number of samples in the original time data block. We can construct a spectrum with N/2 values (magnitudes) corresponding to N/2 discrete frequencies (spectral lines). Phase information can also be derived for each spectral line.

It is important to note that the spectral lines are spaced apart by (sampling frequency/N) and may be considered as "bins", centered on the line frequencies, extending +/- half line spacing. Each FFT bin magnitude represents the total signal energy falling anywhere within its lower and upper bounds.

The spectral line (or bin center) frequencies are not calculated by the FFT algorithm itself but are readily constructed knowing the sampling frequency of the input block. Increasing the sampling frequency alone will increase the spectral line spacing. Increasing N, the number of samples within the time block, while retaining the same sampling frequency, will decrease the spectral line spacing.

The frequency-domain result as calculated using the FFT algorithm produces linear-scaled magnitudes at linear-scaled uniform steps in frequency. It is often helpful to convert the magnitudes into logarithmic-scaled units (e.g. decibels, dB) relative to some reference value. If this value is taken to be 1 V RMS, the units are then identified dBV.

Viewing a spectrum with log Y scale (in dBV) may be helpful, since small signal components can be resolved much more easily than on a linear scale. Logarithmic frequency scaling can also be useful when there are signal components of interest at both lower and upper ends of the spectrum.

ANTI-ALIASING FILTER

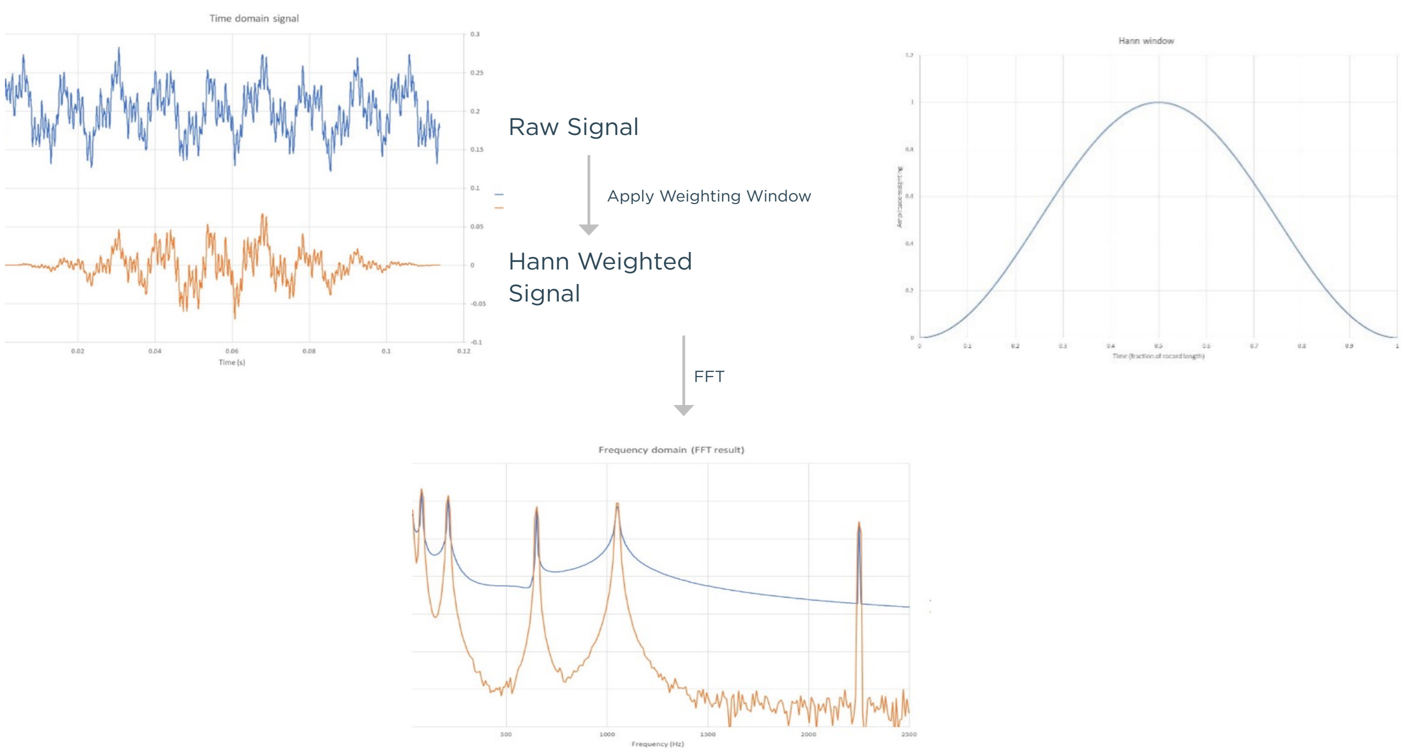
If significant vibration signal energy happens to exist beyond half of the selected sampling frequency, a phenomenon known as aliasing can result. This causes energy to appear in spectral lines (as artefacts) within the FFT effective bandwidth. To prevent or minimize this, a low-pass anti-aliasing filter (AAF) is often applied to the time signal prior to acquisition. The AAF is designed to have very sharp cut-off while retaining as smooth a pass-band response as possible.

When the input time signal comprises an integer number of complete cycles of a sinusoidal signal, the FFT output will show a single spectral line (or bin) with value equal to the RMS value of the input signal, with all other spectral line frequencies showing zero magnitude. If the input signal is not an exact integer number of cycles, then some signal energy will exist at adjacent spectral line frequencies (known as spectral leakage). This situation can be controlled by applying a “window” or weighting function to the time signal prior to FFT processing, as described in the following section.

WEIGHTING WINDOWS

A weighting window is a function applied to a time-domain signal before the Fourier transform. This reduces spectral leakage, which occurs when a signal’s energy is spread across multiple frequency bins due to truncation caused by the finite length of the signal window.

The name “weighting window” comes from the fact that the function applied to the time-domain signal effectively “weights” each sample in the window by a certain amount. The function typically has a bell-shaped curve, with the maximum value at the center of the window and tapering off towards the edges. This weighting function effectively reduces the contribution of samples at the edges of the window, where spectral leakage is most severe. There are several types of windows available, including Hann, flat-top and rectangular. Hann is a commonly used weighting window that provides good spectral resolution while reducing spectral leakage.



In the plot above, the blue line shows the FFT result using rectangular (or no) window. The orange line shows the result using Hann window showing more accurate peak measurement and allowing much better resolution between the peaks.

In summary, to generate the frequency domain representation of a signal, we apply the Fourier transform to a windowed segment of the time-domain signal. The resulting output is a set of complex numbers that represent the frequency content of the input signal, which can be plotted to generate the frequency domain representation.

FREQUENCY DOMAIN ANALYSIS

Once the time signal has been successfully transformed into the frequency domain, specific characteristics can then be examined which may not be readily apparent within the sampled time data.

Often, the lowest significant frequency component will be the machine running speed. Any imbalance will tend to increase this component. Vibration associated with gears, blades/vanes and bearings may be harmonically related to the running speed, and identification of the exact frequencies at which vibration energy is present can help identify the mechanical component involved. A "baseline" spectrum may be acquired and saved as a reference, so that any changes that occur over time can be identified. Machine learning (ML) can be particularly useful in this respect. ML algorithms may extract dozens of features from both time and frequency domains to optimize identification of changes based on the specific waveform or vibration "signature" used in the initial training phase.

EDGE PROCESSING AND AI

Edge computing, machine learning (ML), and artificial intelligence (AI) have significant importance in CBM by enabling real-time analysis, proactive decision-making, and predictive maintenance.

Edge Computing: Edge computing involves processing and analyzing data near the data source, at the "edge" of the network, rather than sending it to a centralized cloud. In CBM, edge computing allows for immediate data analysis and real-time insights directly at the sensor or device level. This reduces latency, enhances responsiveness, and enables timely action without relying on a constant internet connection. Edge computing also helps overcome bandwidth limitations and ensures data privacy and security. An example of edge computing is the implementation of FFT within an accelerometer, so that key spectral features can be extracted and reported periodically, rather than having to transmit full-resolution time-domain data continuously.

Machine Learning (ML): ML algorithms enable CBM systems to learn patterns and correlations within sensor data, leading to automated fault detection, anomaly identification, and performance prediction. ML models can be trained on historical data to recognize complex fault patterns and deviations from normal behavior. By continuously analyzing incoming sensor data, ML algorithms can detect early signs of equipment degradation or impending failures, facilitating timely maintenance actions.

Artificial Intelligence (AI): AI techniques, including deep learning and cognitive computing, enhance CBM by enabling advanced data analysis, decision-making, and optimization. AI algorithms can process large volumes of sensor data, identify hidden patterns, and provide insights into the health and performance of equipment. AI-powered CBM systems can detect emerging trends, identify root causes of failures, and suggest optimized maintenance strategies, ultimately improving equipment reliability and reducing downtime.

The combination of edge computing, ML, and AI in CBM empowers organizations to shift from reactive to proactive maintenance approaches. By analyzing data at the edge, ML and AI algorithms can deliver real-time, actionable insights, allowing for predictive maintenance and minimizing the risk of unexpected equipment failures. This leads to increased operational efficiency, reduced maintenance costs, and improved overall equipment reliability.

CONCLUSION

CBM using vibration sensors is an effective way to monitor the condition of industrial equipment and enable predictive maintenance. With the advent of IoT, wireless communication protocols such as BLE, LoRa, and NB-IoT make data more accessible and economical. VC MEMS and piezo accelerometers are two types of vibration sensors commonly used in CBM, each with their unique advantages. Both time and frequency domain analysis can be used to extract valuable information from the raw vibration data. Edge processing and AI algorithms can analyze sensor data in real-time, enabling early fault detection and predictive maintenance.

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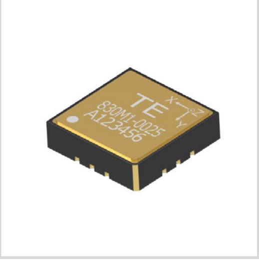
Wireless

LoRaWAN Vibration Sensors

BLE Vibration Sensors



Embedded

805M1

820M1 Single Axis

830M1 Triaxial

Wired 'Plug and Play'

8711

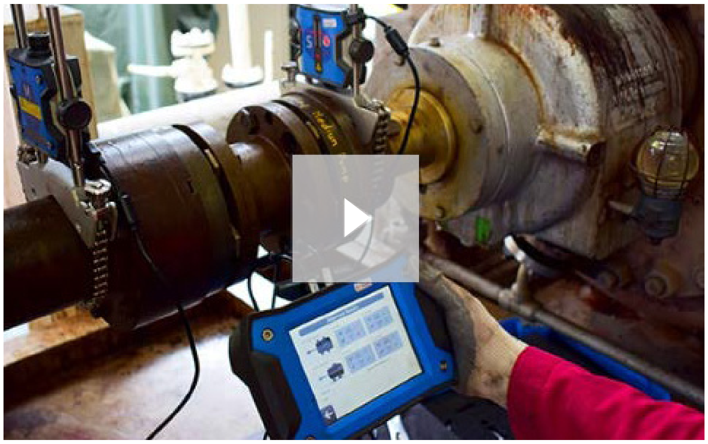
8811

8021

8011

REVOLUTIONIZING INDUSTRY 4.0: ADVANCED VIBRATION SENSING

Explore the future of Industry 4.0 with TE Connectivity's advanced vibration sensors. Join Bernard Kamel, TE Connectivity's Wireless Sensor Engineering Manager, for an insightful journey into how these innovative devices are reshaping maintenance and monitoring practices. Understand their pivotal role in preventing equipment failure and enhancing system performance. Delve into a realm where predictive maintenance aligns with state-of-the-art technology.



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