WHITE PAPER

From Preventive Maintenance to Predictive Maintenance

Why Vibration Sensors Are the Key Enabler of Industrial Condition Monitoring

October 2026

Abstract — Electric drive systems built around asynchronous motors are the workhorse of industrial automation. As these systems have grown more complex, the costs tied to keeping them reliable, safe, and maintained have risen accordingly, making fault diagnosis and prognosis a strategic priority rather than an afterthought [25]. Maintenance practice has followed a clear evolution: from corrective repair to scheduled preventive maintenance, to condition-based maintenance driven by real measurements taken on the running system [25]. Of the sensing technologies available for condition monitoring, vibration analysis alone detects an estimated 90% of the mechanical faults found in rotating machinery [14] — more than any other single technique — which is why this white paper treats vibration sensors as the key enabler of the shift from preventive to predictive maintenance.

1. Preventing Failure Before It Happens: Designing Reliability from Day One

1.1 The Economics of Machine Downtime

Unplanned downtime is a board-level financial exposure, not a minor inconvenience. Aberdeen Research puts the cross-industry average at roughly $ 260,000 per hour, while Siemens' 2024 study found Fortune Global 500 companies lose approximately $ 1.4 trillion a year — about 11% of revenue — to downtime [2], [3]. A 2025 Fluke survey of 600 manufacturing leaders found 55–61% experienced unplanned downtime in the prior year, with almost half reporting six to ten incidents weekly [1]. Capital-intensive sectors are hit hardest: automotive lines lose an estimated $ 2.3 million per hour and semiconductor fabs $ 1.8 million per hour (Figure 1.1) [3].

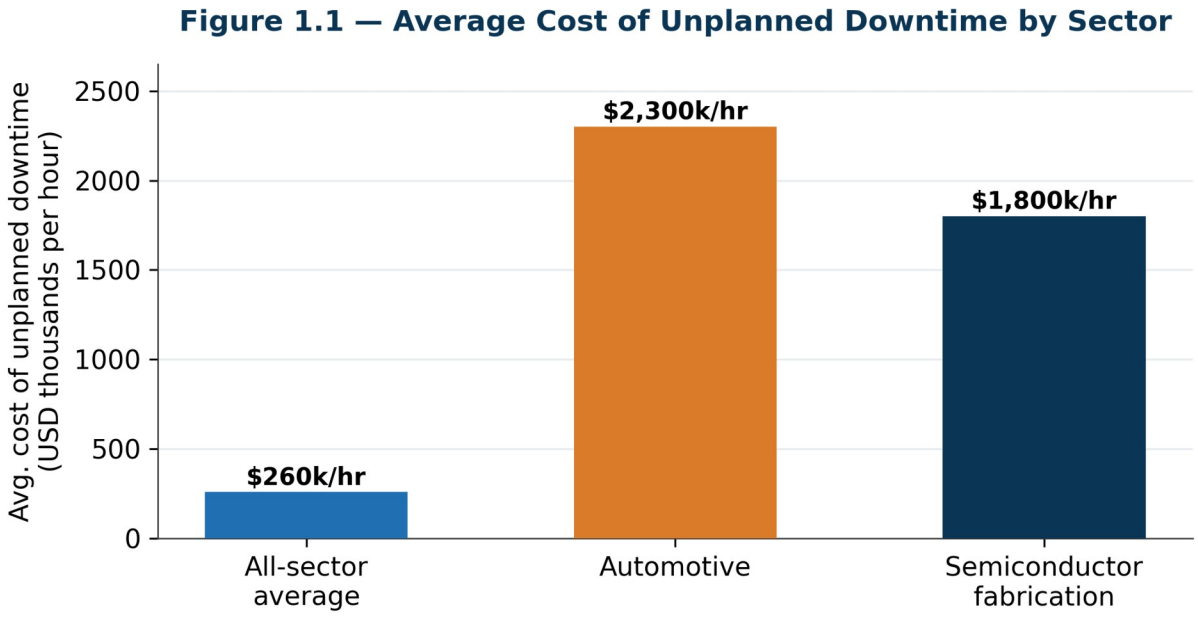


Figure 1.1 — Average cost of unplanned downtime by sector [2], [3].

This is reflected in Overall Equipment Effectiveness (OEE), the standard reliability metric. A World Class OEE of 85%+ is the accepted benchmark, yet the typical plant runs at 40–60% (Figure 1.2) [5], [6]. Unplanned breakdown is consistently the largest single driver of that gap — which is precisely the gap vibration-based condition monitoring is designed to close.

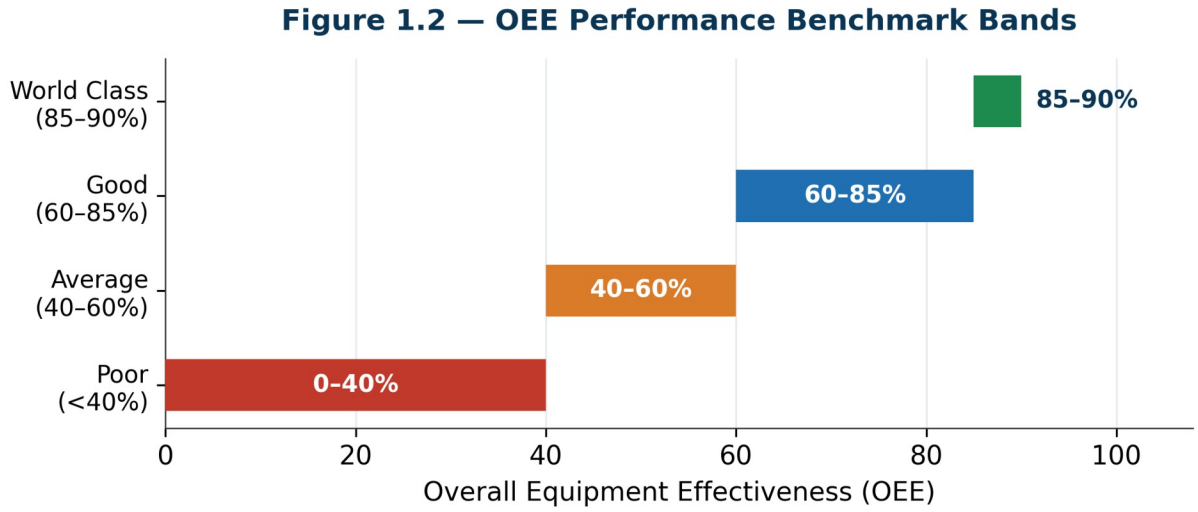


Figure 1.2 — OEE performance benchmark bands, from Poor to World Class [5], [6].

1.2 Common Failure Mechanisms — and Why Vibration Sensors Catch Them

Rotating machinery fails through a small, well-documented set of mechanisms, and field data shows four conditions — unbalance, misalignment, looseness, and bearing wear — account for roughly 90% of faults on rotating equipment [9]. Bearing-related failures alone cause an estimated 40–70% of all rotating-machinery malfunctions, and misalignment is separately implicated in 30–50% of bearing and seal problems (Figure 1.3) [7], [8].

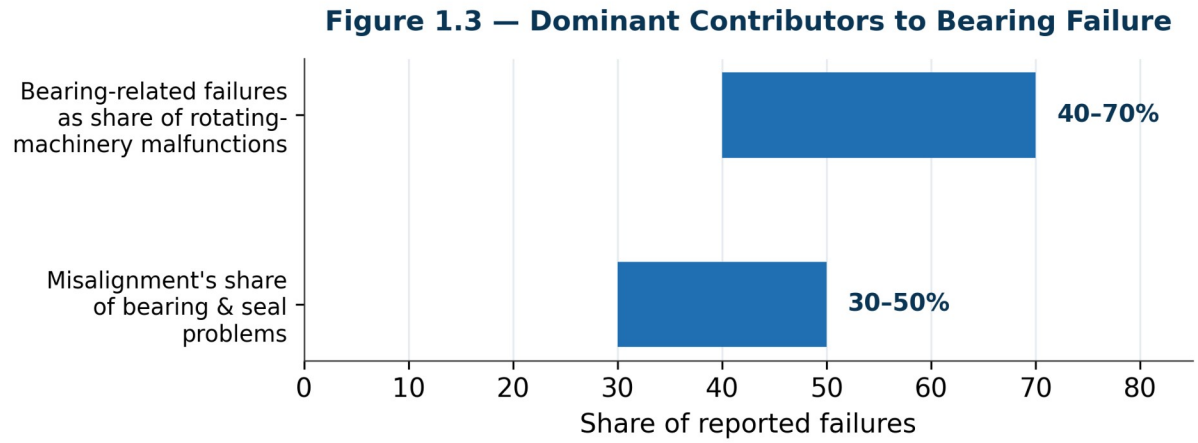


Figure 1.3 — Bearing wear and misalignment are disproportionate contributors to rotating-machinery failure [7], [8].

Failure mechanism	Typical root cause	Vibration signature
Bearing wear	Contamination, poor lubrication, overloading	Broadband high-frequency energy; ball-pass/cage-defect frequencies [8], [9]
Misalignment	Installation offset, thermal growth, pipe strain	Elevated 1× / 2× running-speed amplitude, high axial vibration [9], [20]
Unbalance	Uneven mass distribution, wear, assembly error	Dominant 1× running-speed peak, radial-direction dominant [15]
Mechanical looseness	Loose bolts, worn housing fits	Harmonics of running speed (1×, 2×, 3×…) [9]
Gear degradation	Misalignment, lubrication loss, cyclic overload	Gear-mesh frequency with shaft-rate sidebands [16]

Table 1.1 — Common failure mechanisms in rotating equipment. Every one produces a distinct vibration signature well before it produces a visible symptom.

1.3 Why Failures Still Occur

Reliability built in at design and installation degrades continuously in service: fatigue accumulates, load cycling and operator practice introduce stresses beyond the original design envelope, and environmental conditions accelerate wear. Most of this — early bearing spalling, developing misalignment, incipient looseness — is hidden degradation: it produces no visible symptom until very late in the failure progression.

2. Preventive Maintenance: The Traditional Approach

2.1 What Is Preventive Maintenance?

Maintenance strategy splits into two roots: corrective (act after failure) and preventive (act before it) [25]. Preventive maintenance further splits into **systematic** maintenance — servicing on a fixed time or usage schedule regardless of actual condition — and **conditional (condition-based) preventive maintenance** — servicing only when measured equipment health indicates a need [25]. This section covers systematic PM, the industry baseline for decades; Sections 3–4 cover the condition-based branch, which vibration sensors make practical at scale.

2.2 Benefits and Limitations

Systematic PM reduces catastrophic failures, is easy to plan and budget, and satisfies regulatory inspection requirements. Its structural weakness is that a fixed schedule has no way to know an asset's actual condition, producing two opposite failure modes at once: healthy components are opened up and replaced before the end of their useful life, while faults that develop between two scheduled inspections run to failure undetected [24]. Condition-based maintenance resolves both problems simultaneously by making the trigger for service the machine's measured condition rather than the calendar.

Strategy	Strengths	Weaknesses
Corrective	No spend until failure	High failure risk, production loss, safety risk
Systematic preventive	Fewer catastrophic failures; predictable cost	Services healthy equipment; can induce damage
Conditional preventive	Fewer unplanned failures; service only when needed	Requires upfront sensing investment

Table 2.1 — Strengths and weaknesses of the three root maintenance strategies [25].

2.3 Why Industry Is Moving to Condition-Based Maintenance

Tightening production schedules, a persistent maintenance-labor shortage, and rising service costs are all pushing reliability teams past fixed-interval PM and toward condition-based approaches (Figure 2.1). The rest of this white paper focuses on that condition-based branch — predictive maintenance — and specifically on vibration sensing as its primary, highest-coverage data source.

Figure 2.1 — The Evolution of Industrial Maintenance Strategy



Figure 2.1 — The evolution of industrial maintenance strategy, from run-to-failure to vibration-based prediction.

3. Predictive Maintenance: The Data-Driven Evolution

3.1 What Is Predictive Maintenance?

Predictive maintenance (PdM) is condition-based monitoring taken one step further: sensors — most commonly vibration accelerometers — continuously track a physical parameter, detect the earliest measurable signs of degradation, and project when a component will reach a failure threshold. This combines two capabilities the literature is careful to distinguish: diagnosis (is the asset degraded, and by what fault?) and prognosis (how much time remains before failure?) [25]. Diagnosis tells maintenance planners what is wrong; prognosis, formally defined in ISO 13381-1 as estimating Remaining Useful Life (RUL), tells them how long they have to act.

3.2 The Predictive Maintenance Workflow

A mature PdM program follows the same basic pipeline, shown in Figure 3.1 and formalized by the MIMOSA condition-based-maintenance reference architecture: vibration sensing captures the raw signal; signal processing converts it into usable features (FFT spectra, statistical indicators); diagnosis identifies whether — and which — fault is present; prognosis projects a RUL estimate; and the output becomes a scheduled maintenance action rather than an unplanned stoppage [25]. Vibration is the input that anchors this entire pipeline in the large majority of deployed industrial systems, which is why Section 4 examines it in depth.

Figure 3.1 — The Condition-Based Maintenance Workflow



Figure 3.1 — The condition-based maintenance workflow, anchored on vibration sensing [25].

3.3 Benefits of Predictive Maintenance

The return on PdM is one of the most consistently benchmarked figures in industrial reliability. McKinsey finds PdM cuts unplanned downtime by up to 50% and overall maintenance cost by 18–25% versus preventive baselines [12]; Deloitte documents an 80% downtime reduction and roughly $ 300,000 in savings per asset from a single vibration-monitoring pilot [11]. Independent surveys report that most organizations implementing PdM see positive ROI, with many achieving payback within a year (Figure 3.2) [23].

Figure 3.2 — Impact of Predictive Maintenance Programs

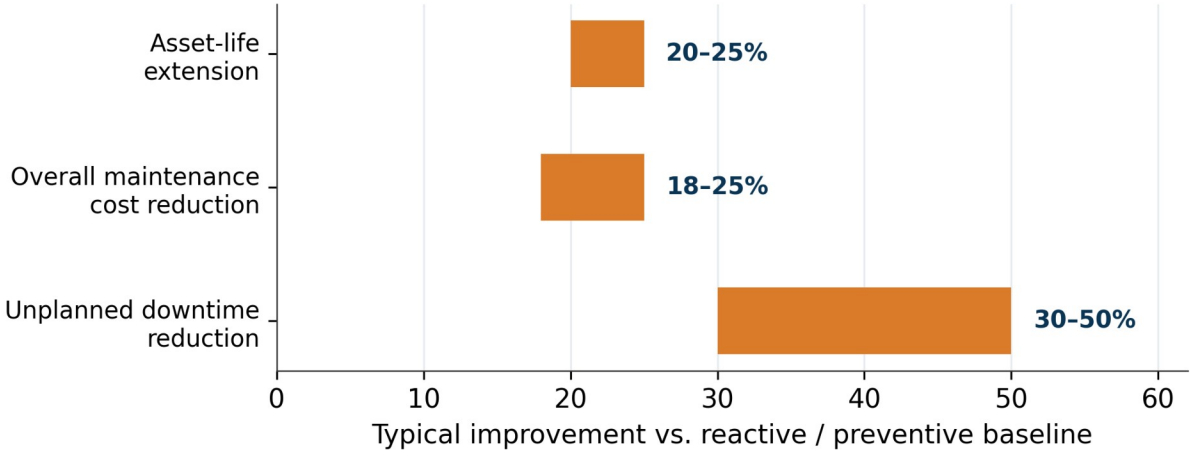


Figure 3.2 — Documented impact of predictive maintenance programs [11], [12].

3.4 Predictive Maintenance and Industry 4.0

PdM is a flagship Industry 4.0 use case because it depends on the same stack: IIoT sensors for continuous data collection, edge analytics to process vibration signals close to the machine, and machine learning to turn trended features into fault classification and RUL estimates. This integration is why the global predictive maintenance market is projected to grow from roughly $ 14.2 billion in 2025 to about $ 98.1 billion by 2033 — a 27.9% CAGR [13] as shown in Figure 4.1.

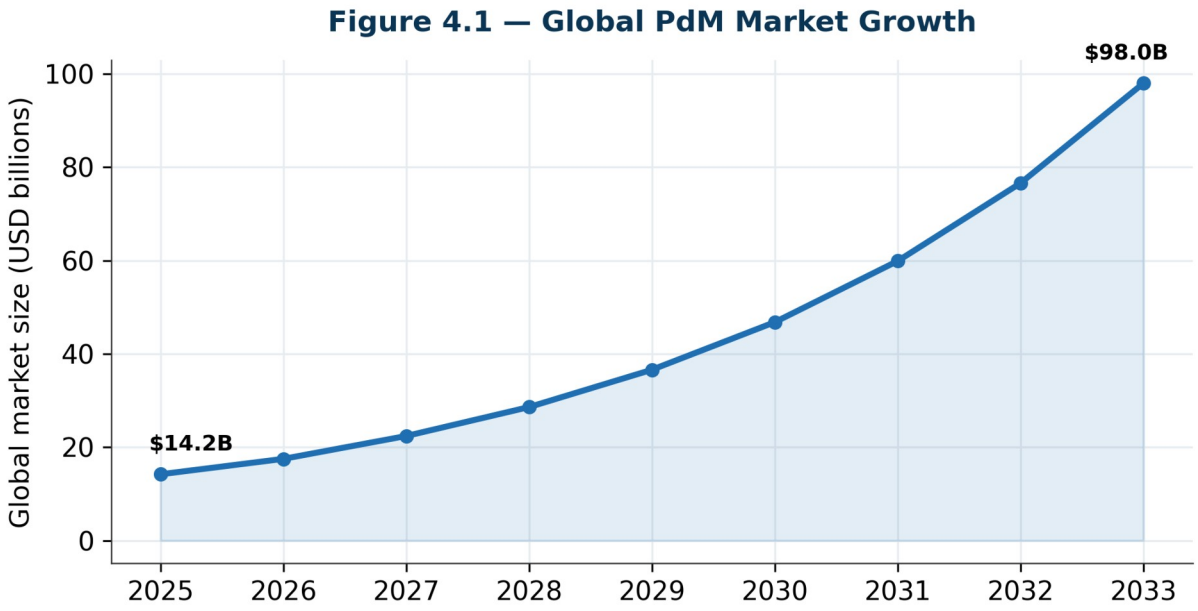


Figure 4.1 — Global predictive maintenance market growth, 2025–2033 [13].

4. Tools and Technologies Enabling Predictive Maintenance

4.1 Condition Monitoring Technologies

No single technique detects every failure mode, so mature programs layer complementary methods. Vibration analysis has the broadest coverage of mechanical faults (imbalance, misalignment, bearing wear, gear defects, looseness). Thermography suits electrical faults and friction-driven heating. Current-signature analysis (MCSA) uses existing electrical infrastructure to catch rotor and stator faults. Acoustic emission often gives the earliest signal of an incipient bearing defect. Oil analysis is the only technique that directly characterizes the contact zone itself [14], [15].

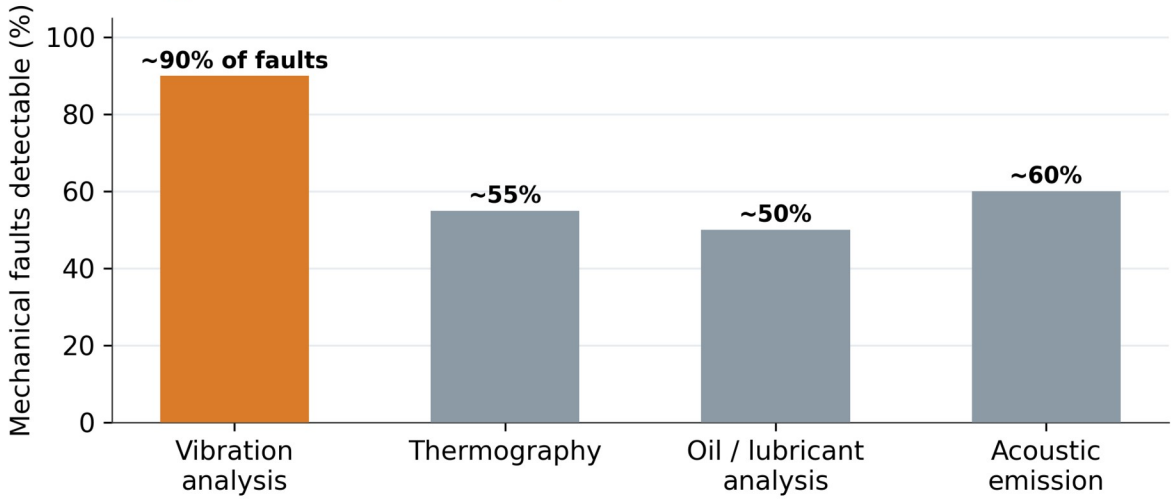
Technology	Primary faults detected	Strength	Typical use
Vibration analysis	Imbalance, misalignment, bearing wear, gear defects, looseness	Broadest fault coverage; continuous, non-invasive monitoring	Motors, pumps, fans, compressors, gearboxes [14]
Thermography	Loose connections, overload, insulation failure	Fast, wide-area, contactless	Electrical panels, bearings [15]
Current monitoring (MCSA)	Broken rotor bars, stator faults, eccentricity	Uses existing electrical infrastructure	Induction motors [10]
Acoustic emission	Early-stage bearing defects, leaks, arcing	Earliest signal, ahead of vibration change	High-speed bearings [15]
Oil analysis	Wear particles, lubricant degradation	Only technique diagnosing the contact zone directly	Gearboxes, hydraulics [15]

Table 4.1 — Complementary condition-monitoring technologies and their diagnostic strengths.

4.2 Why Vibration Sensors Are the Key Enabler

With an estimated 700 million-plus electric motors of varying sizes in service worldwide, and induction motors the dominant prime mover across nearly every sector this white paper has discussed, motor-focused fault detection is one of the highest-leverage applications of predictive maintenance [26]. Vibration analysis is consistently the anchor technology for four reasons: it detects developing faults before they produce a visible performance or temperature symptom; the same accelerometer and analysis method applies across virtually every rotating-machine type; sensors are surface-mounted with no process interruption; and — unlike manual oil sampling or thermography rounds — vibration sensors stream data continuously, enabling trend-based rather than snapshot-based detection. A widely cited review found vibration analysis alone detects approximately 90% of faults observed in rotating machinery (Figure 4.2) [14].

Figure 4.1 — Vibration Analysis Detects ~90% of Mechanical Faults



Source: MDPI review, vibration-based condition monitoring (2022); condition-monitoring technology review [14], [15]

Figure 4.1 — Vibration analysis alone covers approximately 90% of mechanical faults in rotating machinery [14], [15].

A closer look at fault type confirms why: vibration is the leading or a strongly contributing detection method specifically for **bearing faults** and **mechanical coupling/load failures** — the two fault categories Section 1.2 identified as the dominant real-world failure modes — while electrical-signature methods (MCSA, EPVA, IPSA) lead only for faults of electrical origin (Table 4.2) [7], [8], [26].

Fault type	Leading detection method(s)	Vibration relevance
Bearing faults	Vibration; wavelet-on-current; MCSA/EPVA/IPSA	High
Coupling & load failures	Vibration; MCSA/EPVA/IPSA	High
Imbalance or misalignment	MCSA; vibration; EPVA	High
Broken rotor bars	MCSA; EPVA + IPSA	Low — electrical preferred
Stator / insulation faults	EPVA; MCSA; partial discharge	Low — electrical preferred

Table 4.2 — Vibration is the leading method for the two dominant real-world failure categories established in Section 1.2 [7], [8], [26].

This is validated in the field: a Random Forest model trained on industrial-pump vibration data predicted developing faults up to seven days in advance across two and a half years of production use, and comparable vibration-driven models have reported over 90% classification accuracy on equipment ranging from wind-turbine bearings to woodworking machinery [26]. ISO 20816 formalizes how the resulting measurements are interpreted, defining four vibration severity zones that give reliability teams an objective, machine-class-appropriate basis for alarms [18], [19].

4.3 Data Acquisition and Analytics

Between the sensor and the maintenance decision sits a data-acquisition and analytics chain with several distinct layers. Sensors (accelerometers, temperature probes, current transducers) generate the raw signal. Programmable Logic Controllers (PLCs) and data loggers aggregate and buffer readings at the machine or line level, often providing the first stage of alarming against fixed thresholds. Edge devices perform local signal processing — FFT conversion, feature extraction, basic anomaly detection — close to the sensor, which reduces the bandwidth required to move data upstream and allows time-critical alarms to fire without a round trip to the cloud. Cloud connectivity then aggregates edge-processed data across assets, sites, and time for fleet-wide trend analysis, cross-asset benchmarking, and the training of machine-learning models that a single edge device could not support on its own. This tiered architecture — sensor, PLC/edge, cloud — is now the standard reference architecture for Industrial IoT-based predictive maintenance deployments.

The signal-processing stage itself is classically organized into three families of technique [25]. **Time-domain analysis** extracts statistical parameters directly from the raw waveform — RMS (root-mean-square) amplitude, which rises as a machine degrades; kurtosis, which sits near 3 for a healthy signal and rises toward or beyond 4 as impulsive bearing defects develop; crest factor (peak-to-RMS ratio), typically 2–6 for healthy equipment and above 6 in the presence of a localized fault; and skewness, which measures the asymmetry of the signal distribution. These parameters are inexpensive to compute and effective at flagging that degradation is occurring, but on their own they cannot identify which fault is responsible. **Frequency-domain analysis** — most commonly the Fast Fourier Transform (FFT) — resolves the signal into its constituent frequencies, which is what allows a specific fault (e.g., a bearing defect frequency or a gear-mesh sideband) to be identified rather than merely detected; this is the technique underlying the fault-signature identification described in previous section. **Time-frequency analysis** — short-time Fourier transform (STFT), wavelet transforms, and Wigner-Ville distribution — is reserved for non-stationary signals, such as machines under variable speed or load, where a single FFT snapshot cannot capture how the frequency content evolves over time.

Domain	Representative techniques and indicators	Best suited to
Time domain	RMS, kurtosis, crest factor, skewness, variance	Low-cost degradation trending; early warning that something has changed [25]
Frequency domain	Fast Fourier Transform (FFT), spectral analysis	Fault identification under steady-state operation [25]
Time-frequency domain	Short-time Fourier transform (STFT), wavelet transform, Wigner-Ville distribution	Non-stationary signals — variable-speed or variable-load machinery [25]

Table 4.3 — Signal-processing technique families used in vibration-based fault detection [25].

4.4 AI and Machine Learning

Machine learning turns trended vibration features into fault classification and RUL estimates rather than simple threshold alarms. Random Forest is the most frequently top-performing algorithm across independent PdM studies spanning pumps, cutting machines, and induction motors [26], [29], though results are task-dependent — one multi-sensor AC-motor study found a K-Nearest Neighbors classifier reaching 100% test accuracy, ahead of Random Forest (95%) and SVM (83.7%) [27]. RUL estimation remains an active research area spanning classical degradation models to deep learning [16], [17]; notably, even research exploring lower-cost electrical-signal alternatives to accelerometers explicitly frames vibration-based monitoring as the accuracy benchmark it is trying to approach [28] — underscoring vibration's role as the reference-standard sensing modality for predictive maintenance.

4.5 Critical Vibration Sensor Performance Parameters

The accuracy of every downstream analytics step is bound by the physical performance of the vibration sensor generating the data. Five parameters determine whether a given sensor is fit for industrial deployment [21], [22]:

- Frequency response — the usable range, typically 0.2 Hz–1 kHz for general-purpose monitoring up to 10 Hz–15 kHz+ for bearing/gear diagnostics
- Sensitivity — the mechanical-to-electrical conversion factor, typically 10–500 mV/g, matched to the expected vibration amplitude
- Dynamic range — the span between noise floor and overload point, so both incipient faults and high-amplitude alarms are captured without clipping
- Long-term stability — resistance to sensitivity drift over years of service, essential since drift is indistinguishable from genuine degradation in trend data
- Environmental resistance — IP-rated sealing, wide operating-temperature range, and shock tolerance for the installation site

Parameter	What it determines	Typical industrial range
Frequency response	Which fault types the sensor can resolve	0.2 Hz–1 kHz up to 10 Hz–15 kHz+ [21], [22]
Sensitivity	Signal resolution for the application	10–500 mV/g [20], [22]
Dynamic range	Capturing low-level faults and high alarms together	Set by sensor full-scale range [20]
Long-term stability	Reliability of trend data over years	Low specified sensitivity drift [21]
Environmental resistance	Survivability on site	IP66/IP68; wide temp range; high shock [22]

Table 4.3 — Critical vibration-sensor performance parameters for industrial condition monitoring.

5. YAGEO Group's Piezoelectric Vibration Sensors for Predictive Maintenance

5.1 Why Vibration Monitoring Matters

Section 4 established, from independent academic and industry literature, why vibration analysis is the highest-coverage detection method available for rotating machinery. The remainder of this white paper turns from that general case to a specific, deployable answer: YAGEO Group's VS Series piezoelectric vibration sensors. Unlike periodic manual inspection, a permanently installed vibration sensor gives continuous visibility into machine condition, and — combined with the Industrial IoT connectivity described in Section 4.3 — turns that visibility into an automated, always-on predictive maintenance capability rather than a periodic spot check.

5.2 YAGEO Group's VS Series Technology Overview

YAGEO Group's VS Series piezoelectric vibration sensors are purpose-built for real-time monitoring of industrial equipment & machinery. The sensors are based on piezoelectric technology: mechanical vibration deforms a piezoelectric ceramic element, generating an electrical output proportional to vibration amplitude (Figure 5.1). This makes piezoelectric sensing particularly well suited to the higher-frequency mechanical vibration — bearing defects, friction, cavitation, gear wear — that Section 4.2 identified as vibration analysis's core strength.

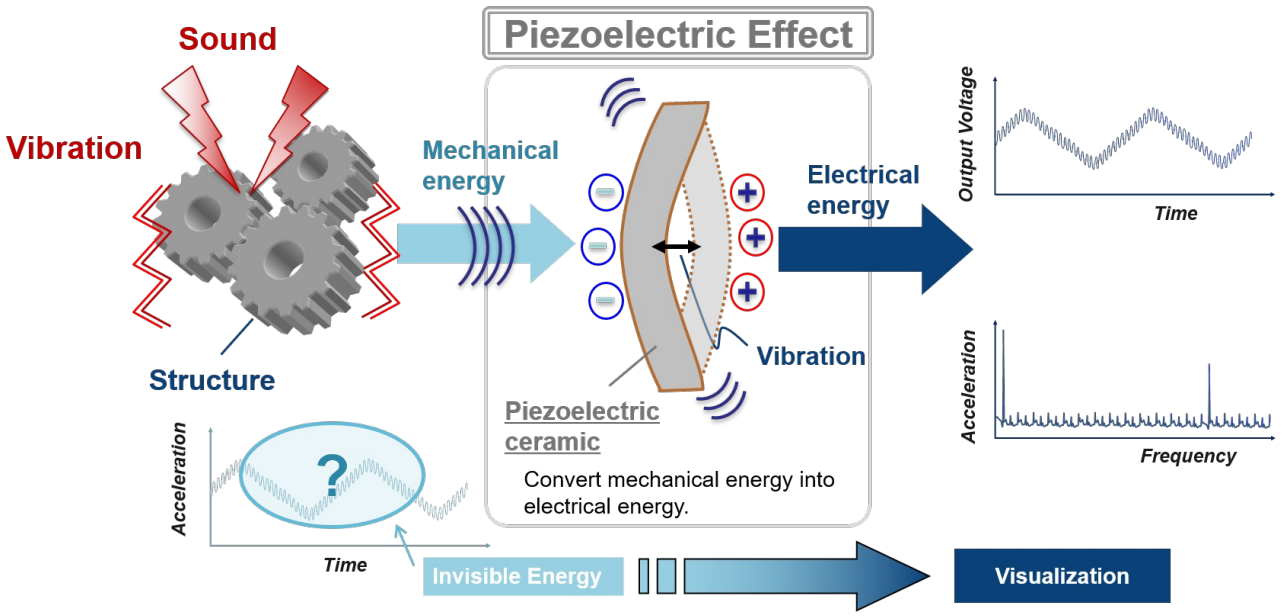


Figure 5.1 — The piezoelectric effect: mechanical vibration energy is converted directly into an electrical output signal.

YAGEO Group uses a bending-type piezoelectric sensor structure that combines compact size, high sensitivity, and simple construction.

A key differentiator of the VS series is the combination of optimized piezoelectric ceramic materials with a proprietary vibration-amplification mechanism, delivering high sensitivity while maintaining a wide usable frequency range. The sensor incorporates a built-in amplifier, enabling direct voltage-output operation from a low-voltage supply — connecting straight to PLCs, microcontrollers, and other Industrial IoT hardware without external charge amplifiers or signal-conditioning equipment, which meaningfully simplifies deployment at scale.

5.3 Technical Advantages of YAGEO Group's VS Sensors

Effective predictive maintenance requires sensors capable of resolving both low-level and high-frequency vibration across a broad operating range. The VS Series covers a frequency response of 10 Hz to 15 kHz across its entire product line — placing it at the high-bandwidth end of the general industry range summarized in Table 4.3, and specifically optimized for bearing- and gear-defect detection (Figure 5.2). A single sensor platform can

therefore monitor base looseness, rotating-equipment imbalance, coupling misalignment, gear-mesh defects, and bearing wear and surface damage — fault types that occur across different frequency bands, making wideband coverage valuable in practice.

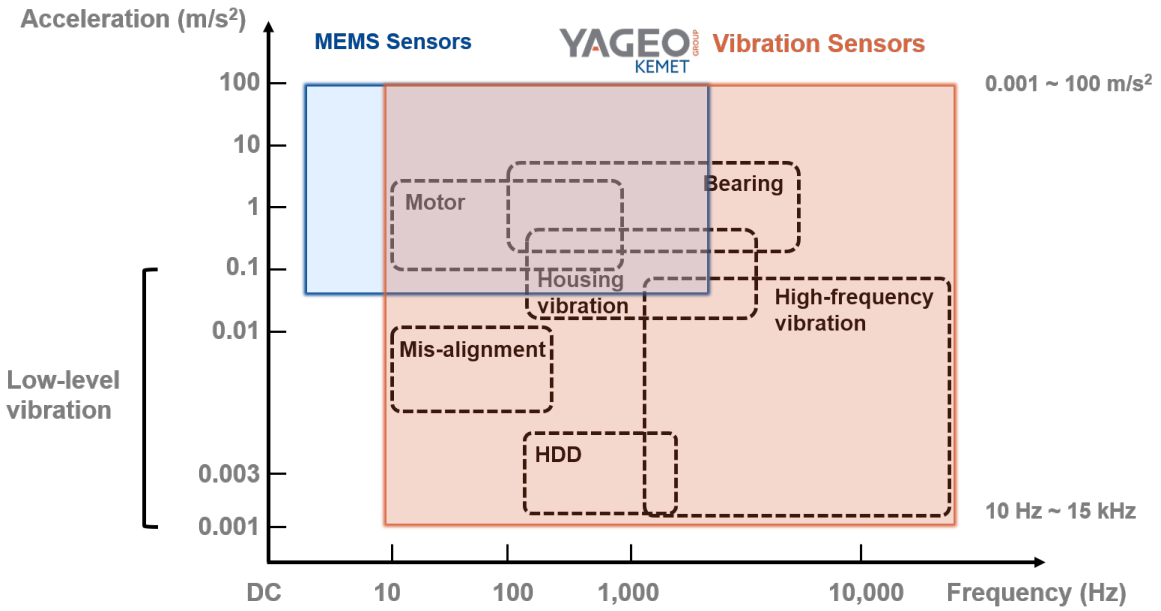


Figure 5.2 — YAGEO Group's VS Series frequency and acceleration coverage versus conventional MEMS sensors [company data].

Sensitivity is the second critical parameter: VS Series sensors achieve up to twenty times the sensitivity of conventional sensors through optimized ceramic composition and the proprietary amplification structure, improving the ability to catch low-level vibration before degradation becomes severe. The product portfolio spans three models, tuned to different monitoring needs (Table 5.1).

Model	Sensitivity	Measurement range	Best suited to
VS-JV10A	10 mV/(m/s²)	±100 m/s²	Balanced sensitivity/range; general-purpose PdM
VS-JV02A	2 mV/(m/s²)	±500 m/s²	Wider dynamic range; high-vibration or overload-prone assets
VS-BV203-B	20 mV/(m/s²)	±50 m/s²	Highest sensitivity; early-stage fault detection

Table 5.1 — YAGEO Group's VS Series product portfolio. All models share a 10 Hz–15 kHz frequency response.



Figure 5.3 — VS-JV02A / VS-JV10A: metal-encapsulated, waterproof and oil-resistant, built-in amplifier, detachable cable.



Figure 5.4 — VS-BV021 / VS-BV203-B: small and thin form factor with built-in amplifier and integrated cable.

The JV type models add a rugged metal housing, detachable cable design, IP67-equivalent protection, and a −25°C to +85°C operating range for demanding industrial environments; the BV type trades housing ruggedness for a smaller, thinner form factor suited to space-constrained mounting points.

A practical barrier to piezoelectric vibration sensing has traditionally been the need for external charge amplifiers, signal conditioners, or dedicated vibration analyzers before the data is usable — adding cost and complexity to every installation. The VS Series addresses this directly: its integrated amplifier operates from a simple 3 V–5.5 V supply and outputs a ready-to-use voltage signal centered on a stable offset — approximately 1.5 V for JV type models, roughly half the supply voltage for BV type models. Mechanical vibration appears as an AC component around that offset, and amplitude is derived directly from the sensor's rated sensitivity (Figure 5.5). This lets the sensor connect straight to a PLC analog input, an edge-computing device, or an IIoT gateway — in practice meaning simpler wiring, lower total system cost, faster deployment, and straightforward integration into existing automation infrastructure.

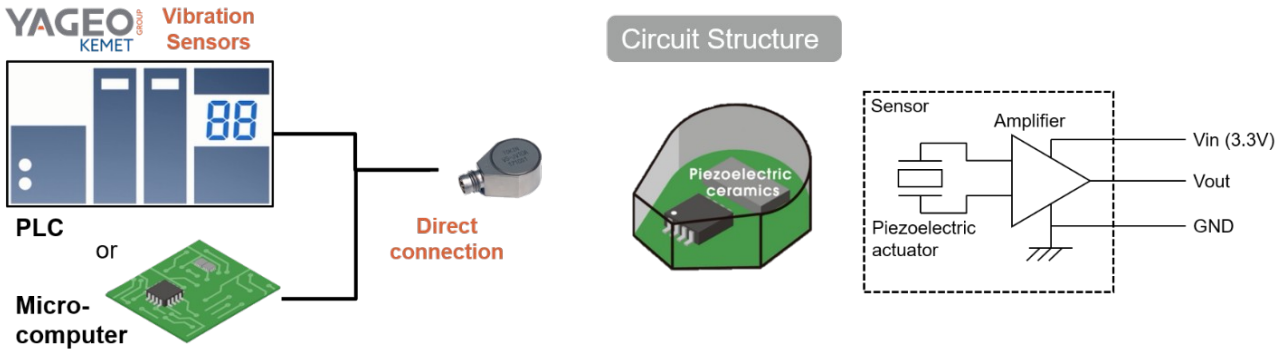


Figure 5.5 — Direct sensor-to-PLC/microcontroller connection enabled by the VS Series' integrated amplifier circuit.

5.4 Typical Predictive Maintenance Applications

The following measurements, performed by YAGEO Group's engineering team, demonstrate how VS Series sensors distinguish normal from abnormal operating conditions using waveform comparison and Fast Fourier Transform (FFT) analysis. They illustrate a method rather than universal diagnostic thresholds: reference values must always be established for the specific equipment, installation, and operating conditions being monitored.

Pump Monitoring. Pumps commonly experience bearing wear, cavitation, imbalance, and mechanical degradation, often producing elevated vibration before flow performance is noticeably affected. In this measurement, a VS-BV203 sensor (double-sided-tape mounted) compared the vibration waveforms of two pumps with different operating sounds. A clear difference appeared in both the time and frequency domains: the noisier pump showed stronger high-frequency vibration components, consistent with a worn bearing (Figure 5.6). This type of comparison can establish an equipment-specific baseline against which future measurements are evaluated for changes in vibration level or frequency content.

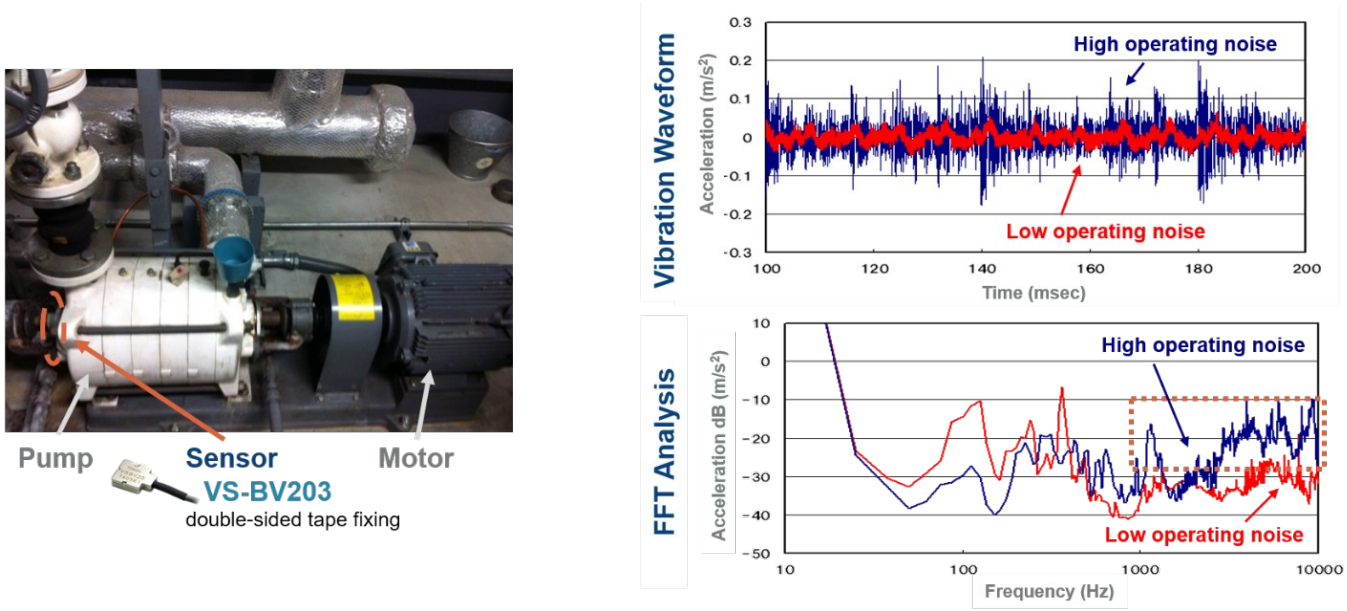


Figure 5.6 — Pump vibration measurement and FFT comparison, VS-BV203 sensor [YAGEO Group engineering data].

Motor Looseness Detection. Electric motors are among the most frequently monitored predictive-maintenance assets, and failures often begin with subtle changes in bearing condition or mounting integrity — changes high-frequency vibration analysis can catch earlier than temperature or current monitoring alone. Here, a VS-JV10A

sensor was magnet-mounted on a motor, and vibration was compared between a firmly fixed bearing housing and the same housing deliberately loosened. FFT analysis showed many additional peaks in the 500 Hz–1 kHz band once the fixation was loosened (Figure 5.7) — a difference invisible in overall vibration amplitude alone, and a reminder that consistent sensor placement and mounting method matter for reliable trending. Measurements intended for trending should therefore be performed with the same sensor location and installation method whenever possible. Installing the sensor firmly on a hard, flat surface and positioning it as close as possible to the measurement point is highly recommended.

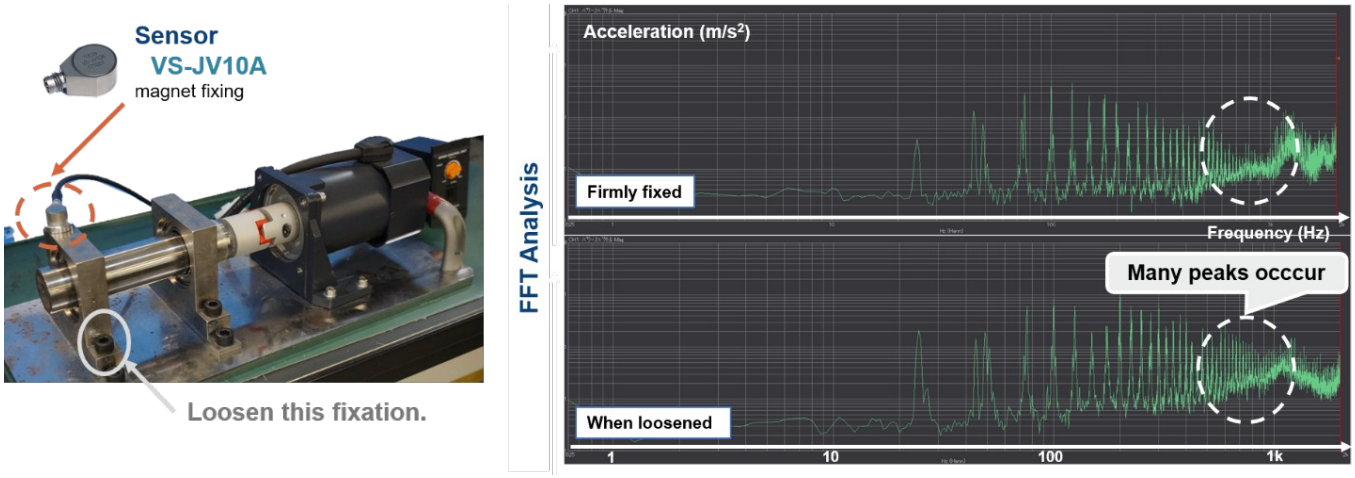


Figure 5.7 — FFT comparison of firmly fixed versus loosened motor conditions, VS-JV10A sensor [YAGEO Group engineering data].

Bearing Damage Detection. Bearings are among the most common failure points in rotating equipment, and rolling-element bearings generate distinctive vibration changes as their surfaces degrade. In this comparison, a VS-BV203 sensor measured bearings with and without ball damage. The damaged bearing produced a larger time-domain output swing and a clearly identifiable FFT peak around 1.6 kHz, while the healthy bearing showed a markedly lower response (Figure 5.8). As with the other examples, a threshold derived from one machine should not be applied to another — equipment construction, speed, load, sensor position, and environment all influence the vibration signature, so baselines and thresholds should be established under representative operating conditions for each monitored asset.

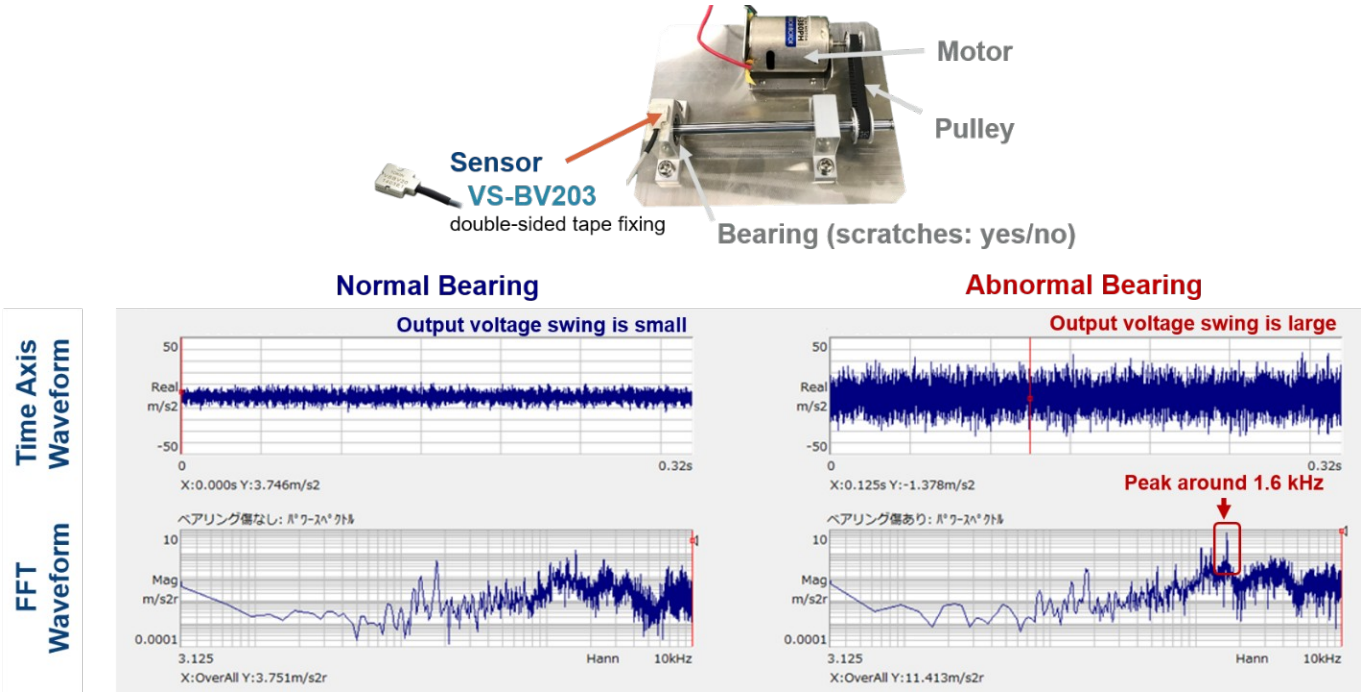


Figure 5.8 — Comparison of normal and damaged bearing vibration, VS-BV203 sensor [YAGEO Group engineering data].

5.5 Key Insights from the Case Studies

Mechanical faults produce detectable changes before failure. All three case studies generated measurable vibration-signature changes ahead of any functional symptom: the noisier pump showed elevated high-frequency components, the loosened motor produced additional peaks near 500 Hz–1 kHz, and the damaged bearing generated both larger amplitudes and a distinct 1.6 kHz peak.

FFT analysis adds diagnostic value beyond overall vibration level. Measuring vibration magnitude alone shows that something changed; frequency-domain analysis shows where. Trend changes within specific frequency bands are consistently more actionable than monitoring total vibration alone.

High-frequency monitoring is particularly valuable for bearing health. Both the pump and bearing studies showed their clearest differences at higher frequencies, consistent with the broader principle that bearing degradation generates high-frequency vibration components well before damage becomes visible.

Baseline measurements are essential. None of the case studies relied on an absolute vibration value; each compared a known-good condition against a known-abnormal one. Machine-specific baselines, tracked over time, are more valuable than generic alarm thresholds, since vibration levels depend on equipment design, speed, mounting, and installation environment.

5.6 From Sensor Data to Predictive Maintenance Decisions

The value of vibration monitoring is ultimately determined not by the sensor alone but by how effectively the collected data becomes a maintenance action. A typical VS Series predictive-maintenance workflow mirrors the condition-based architecture introduced in Section 3.2: continuous vibration acquisition, signal filtering and FFT processing, baseline creation, trend monitoring, threshold evaluation, and maintenance recommendation. Sensor output can be collected through PLCs, IIoT gateways, edge computers, or centralized monitoring platforms, and

once digitized, FFT analysis lets maintenance teams observe vibration energy across distinct frequency bands (Table 5.2).

Frequency range	Potential failure mechanism
10–50 Hz	Loose bases and structural issues
30–100 Hz	Equipment imbalance
50–200 Hz	Coupling misalignment
1–5 kHz	Gear defects
3–10 kHz	Bearing wear and abrasion

Table 5.2 — Frequency bands typically associated with specific failure mechanisms, consistent with the qualitative vibration signatures identified in Table 1.1.

These frequency-to-fault relationships let maintenance teams move beyond simple threshold alarms toward genuine fault identification and diagnosis. As Industrial IoT and machine learning continue to mature, the availability of reliable, high-quality vibration data becomes the limiting factor for predictive maintenance performance. By combining wide frequency coverage, high sensitivity, integrated signal conditioning, and straightforward integration into automation systems, YAGEO Group's VS Series provides exactly that: a practical, deployment-ready sensing platform for modern predictive maintenance.

6. Conclusion

This white paper has traced predictive maintenance from first principles to field-proven practice. Unplanned downtime remains one of the largest controllable costs in industrial operation, and the great majority of that cost traces back to a small set of mechanical failure mechanisms — bearing wear, misalignment, unbalance, and looseness — that develop gradually and announce themselves, almost without exception, as a change in vibration long before they announce themselves any other way (Sections 1–2). Predictive maintenance built on continuous, vibration-based condition monitoring is the strategy the data supports: it cuts unplanned downtime by up to 50% and overall maintenance cost by 18–25% against preventive baselines, with vibration analysis alone accounting for roughly 90% of detectable mechanical faults across the published literature (Sections 3–4). YAGEO Group's VS Series piezoelectric vibration sensors translate that evidence into a deployable product: wideband 10 Hz–15 kHz coverage, sensitivity tuned across three models, and an integrated amplifier architecture that removes the traditional cost and complexity barriers to piezoelectric sensing — validated in this paper's own pump, motor, and bearing measurements (Section 5). As Industrial IoT and machine learning continue to grow the predictive maintenance market toward a projected $ 98 billion by 2033 [13], the sensor at the base of that stack matters more, not less. Vibration monitoring is not one option among several for industrial condition monitoring — it is, on the evidence assembled in this paper, the key enabler, and YAGEO Group's VS Series is built specifically to deliver it.

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