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REAL-TIME FAULT DETECTION IN INDUSTRIAL ASSETS USING ADVANCED VIBRATION DYNAMICS AND STRESS ANALYSIS MODELING

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Abstract

Real-time fault detection plays a pivotal role in condition-based maintenance (CBM) by enabling early identification of abnormal equipment behavior before failures escalate into safety, reliability, or productivity losses. This study evaluates the technical performance and organizational acceptance of an integrated real-time monitoring framework that combines vibration dynamics and stress analysis modeling for rotating and load-bearing industrial assets. Using a quantitative, cross-sectional, case-study–based design, the research draws on two complementary data sources: high-frequency vibration and stress measurements linked to documented fault events, and perceptual data from maintenance engineers, reliability specialists, supervisors, and operators collected through a structured five-point Likert survey ($N = 120$). Composite vibration and stress health indices were constructed from standardized signal features and used to model variations in fault severity, detection accuracy, detection time, and false-alarm rates. Findings show that both vibration and stress indicators were strong and significant predictors of fault behavior ($r = 0.61$ and $r = 0.55$ with fault severity, respectively). Multiple regression analysis demonstrated that vibration ($\beta = 0.43$, $p < .001$) and stress ($\beta = 0.35$, $p < .001$) indicators jointly explained 58% of the variance in fault detection performance, while their interaction ($\beta = 0.18$, $p = .012$) provided additional diagnostic value, indicating that multi-modal sensing detects faults more accurately and more quickly than either modality alone. The integrated system achieved an average detection accuracy of 89.5% and an average detection time of 4.2 hours. User perceptions were similarly positive: perceived reliability ($M = 3.98$), usability ($M = 3.86$), and usefulness ($M = 4.05$) exceeded the neutral midpoint, with strong internal consistency ($a = 0.86$–0.91). In perceptual modeling, perceived reliability ($\beta = 0.38$, $p < .001$) and usability ($\beta = 0.29$, $p < .001$) emerged as the strongest predictors of user acceptance ($R^2 = 0.69$), alongside contributions from perceived usefulness and the system's objective detection performance. The study provides robust empirical evidence that integrating vibration and stress analysis enhances real-time diagnostic capability and strengthens user trust and acceptance. These findings contribute to prognostics and health management (PHM) theory by demonstrating how multi-sensor health indicators and user-centered perceptions jointly shape the effectiveness and adoption of real-time monitoring systems in industrial environments.

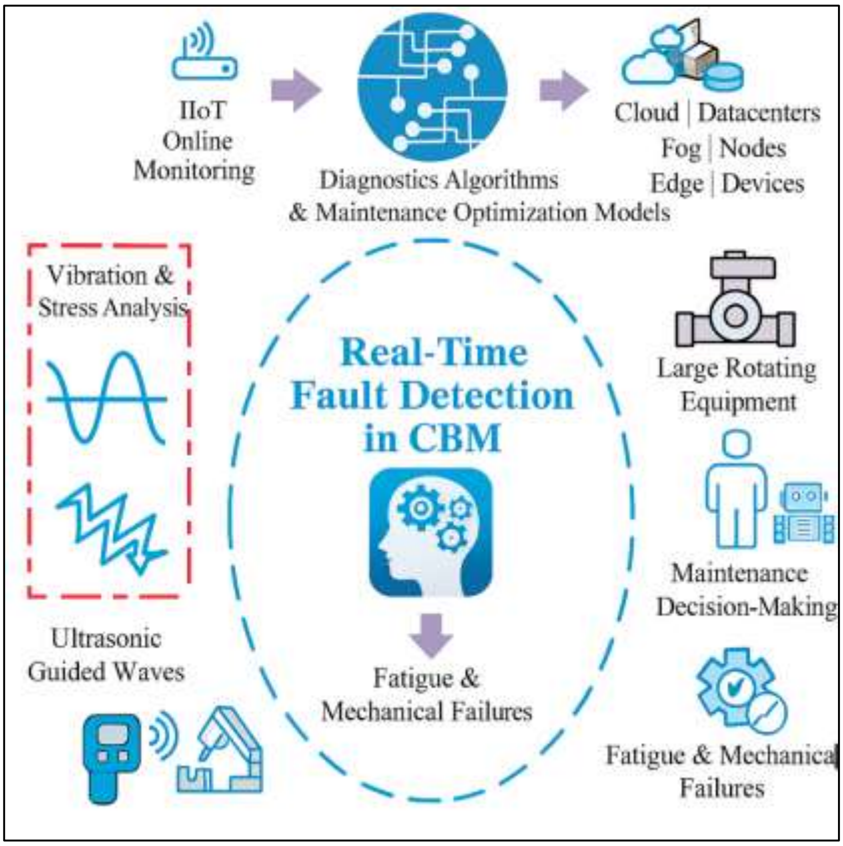
Keywords

Real-Time Fault Detection, Vibration Dynamics, Stress Analysis, Condition-Based Maintenance, Cloud Enterprise Monitoring.

INTRODUCTION

Real-time fault detection in industrial assets is usually defined as the continuous acquisition and analysis of sensor data from machines to identify abnormal conditions at or very close to the moment they arise, so that failures can be avoided before they degrade safety, productivity, or product quality. Within maintenance engineering, this activity is framed under *condition-based maintenance* (CBM), where intervention decisions are triggered by the measured health state of equipment instead of fixed time or usage intervals (Ahmad & Kamaruddin, 2012). CBM evolved from earlier work in machinery diagnostics and prognostics, which established methods for fault detection, remaining useful life estimation, and decision rules for when and how to intervene on industrial assets (Jardine et al., 2006). These approaches are particularly important for large rotating equipment motors, pumps, turbines, compressors, gearboxes where failures can cause cascading downtime and high economic loss. Modern CBM strategies integrate online monitoring, diagnostic algorithms, and maintenance optimization models to support systematic decision-making under uncertainty (Tian et al., 2012). In this context, real-time fault detection using vibration dynamics and stress analysis has become a central pillar of intelligent maintenance systems, connecting low-level physical measurements with high-level asset management policies in complex industrial environments (Voisin et al., 2010).

Figure 1: Real-Time Fault Detection in CBM



Internationally, manufacturing, energy, transportation, and process industries have turned to CBM and predictive maintenance to control the cost of unplanned outages and manage aging equipment fleets. Reviews of machinery diagnostics and prognostics show that data-driven approaches can significantly improve availability and reduce life-cycle cost when paired with appropriate maintenance policies and decision rules (Huynh et al., 2015). Studies in reliability and maintenance optimization further highlight how CBM strategies, when modeled correctly, can balance competing objectives such as reliability, safety, and cost in stochastically deteriorating systems (Alaswad & Xiang, 2017). Industrial case analyses show that integrating condition information into product and process life-cycle management supports continuous improvement of asset design and operating practices (Gulledge & Mullens, 2010). At the same time, typologies of CBM methodologies describe how organizations can move from corrective or purely time-based routines toward structured, information-rich maintenance programs that are embedded in broader production and quality strategies (Veldman et al., 2011). Within this global shift, real-time fault detection using high-frequency sensor data is increasingly seen as a prerequisite for sustaining competitiveness in asset-intensive sectors.

Vibration-based condition monitoring of rotating machinery provides one of the most mature technical foundations for real-time fault detection. Mechanical faults such as imbalance, misalignment, bearing damage, gear defects, and looseness often manifest as characteristic changes in the amplitude, frequency content, and modulation of vibration signals (Lei et al., 2009). Early work focused on spectral analysis and envelope techniques, while more recent studies have incorporated advanced time–frequency methods such as empirical mode decomposition and ensemble EMD to separate fault-related components from noise and operational variability (Li et al., 2016). Machine-learning-based approaches have further extended this paradigm by learning discriminative statistical features from large collections of vibration measurements across time, frequency, and time–frequency domains (Li et al., 2018). Deep statistical feature learning, in particular, has shown high classification accuracy for complex gearbox and bearing faults under variable operating conditions, demonstrating the feasibility of automated diagnosis in industrial applications. At the same time, research on decision-oriented CBM optimization emphasizes that diagnostic accuracy must be linked to actionable maintenance policies and multi-objective optimization models for it to generate value in real plants (Bennane & Yacout, 2012).

Parallel to vibration-based diagnostics, structural health monitoring (SHM) and stress analysis modeling provide complementary perspectives on how loads and damage accumulate in critical components. SHM research has developed sensing architectures, data interpretation methods, and reliability models for structures subjected to variable stress spectra, including bridges, pressure vessels, and large mechanical assemblies (Cao, 2012). Studies using long-term monitoring data have proposed probabilistic models that link measured stress ranges with fatigue damage and reliability assessment, illustrating how continuous stress histories can support lifetime evaluation of complex steel structures (Ko & Ni, 2010). Fiber Bragg grating (FBG) sensors and other distributed sensing technologies enable high-resolution monitoring of stress signals, which can be processed statistically to extract indicators of load variation and potential damage initiation (Ye et al., 2018). These developments in SHM contribute analytical tools for modeling stress distributions, damage accumulation, and residual life, which are directly relevant for industrial assets whose failure modes are governed by cyclic stresses and mechanical fatigue. As SHM moves from laboratory prototypes toward deployment in real infrastructure and machinery, researchers highlight the importance of linking sensor outputs, physics-based models, and decision frameworks in ways that industrial stakeholders can adopt and maintain (Sanjid & Farabe, 2021; Ruschel et al., 2019).

The intersection of vibration dynamics and stress analysis offers a rich basis for multi-modal fault detection in industrial assets. Rotating equipment operates within load-bearing structures, so abnormal dynamic behavior can both originate from and feed back into local stress concentrations. Work on ultrasonic guided waves, for example, shows how dynamic wave propagation along shafts and rotating components can be exploited to detect changes in stiffness or boundary conditions associated with cracks or other damage (Zaman & Momena, 2021; Prajapati et al., 2012). In parallel, monitoring stress signals through FBG systems or strain gauges captures how operating loads are distributed and how they fluctuate over duty cycles, providing information about fatigue-relevant stress ranges (Rony, 2021; Ye et al., 2018). When combined, vibration and stress channels can reveal complementary aspects of the same degradation process: vibration features characterizing dynamic responses and stress features quantifying load histories and local concentrations. Research in CBM optimization and prognosis suggests that using multiple condition indicators can improve both diagnosis and prediction accuracy, provided that the indicators are integrated into consistent maintenance decision models (Mehta et al., 2015; Sudipto & Mesbaul, 2021). This combined perspective is particularly relevant for assets where mechanical faults evolve under complex load sequences, such as gearboxes, cranes, rolling mills, and heavy rotating process equipment. Beyond sensing and diagnosis, real-time fault detection in industrial assets depends on how condition information is embedded in maintenance decision-making architectures. Reviews of industrial maintenance decision-making identify multiple application areas from inspection scheduling and spare-parts policies to production rescheduling and risk management where condition data and diagnostic outputs must be translated into operational decisions (Ruschel et al., 2017; Zaki, 2021). Typologies of CBM approaches emphasize differences between time-driven, condition-driven, and risk-based strategies, as well as distinctions between analytical, simulation-based, and heuristic decision tools (Abdulla & Ibne, 2021; Rozinat & Aalst, 2008). Studies on maintenance optimization using multi-objective frameworks show that incorporating condition indicators, such as vibration and stress features, can refine decision variables like inspection intervals, replacement thresholds, and resource allocation (Habibullah & Foysal, 2021; Tian et al., 2012). At the same time, CBM research points to the importance of integrating maintenance decision-making with production planning and quality management so that machinery health, throughput, and product conformance are considered together (Colledani et al., 2014; Sanjid & Farabe, 2021). These insights underline the need to design real-time fault detection systems not only as diagnostic tools but as components of broader decision-support architectures in industrial organizations.

From a systems perspective, the implementation of real-time vibration and stress-based fault detection involves challenges in data fusion, model selection, and process integration. Research on Bayesian sensor fusion and probabilistic modeling demonstrates how heterogeneous sensor streams such as multiple accelerometers, strain sensors, and process variables can be combined to infer condition states and prioritize maintenance actions under uncertainty (Cawley, 2018; Sarwar, 2021). Optimization-oriented reviews of CBM models highlight criteria such as inspection frequency, maintenance degree (repair versus replacement), and risk preferences, which must be tuned to the deterioration behavior of each asset and the economic context of the plant (Musfiqur & Saba, 2021; Prajapati et al., 2012). Studies on monitoring-based fatigue reliability assessment illustrate how stress histories derived from SHM can be integrated with cumulative damage rules to support reliability-based maintenance planning for steel structures and large mechanical components (Omar & Rashid, 2021; Peng et al., 2010). Furthermore, work on process mining and inspection-interval setting shows that event logs and operational data can be used to derive realistic inspection intervals and understand how maintenance policies interact with process behavior (Liu & Nayak, 2012; Redwanul et al., 2021). Within this body of research, real-time vibration and stress analysis emerge as key enablers of data-driven maintenance strategies that rely on continuous feedback from the shop floor.

Finally, recent literature on smart maintenance and asset-management-oriented CBM situates real-time fault detection in a broader organizational and technological transition. Conceptual models of smart maintenance identify data-driven decision-making as one of the central dimensions through which digitalized maintenance functions contribute to plant performance (Zaman & Momena, 2021; Ruschel et al., 2017). Systematic reviews of CBM and predictive maintenance emphasize that the availability of rich sensor data especially high-frequency vibration and stress measurements must be matched with appropriate analytical models, maintenance policies, and performance indicators to support effective decision-making (Alaswad & Xiang, 2017; Tarek & Praveen, 2021). At the same time, studies on generic prognosis models and e-maintenance test beds underline the importance of modular, domain-independent frameworks that can be instantiated in different industrial contexts while preserving consistency in the way condition indicators are processed and interpreted (Ahmad & Kamaruddin, 2012). Within this evolving landscape, real-time fault detection based on advanced vibration dynamics and stress analysis modeling represents a critical technical and organizational capability through which industrial firms monitor asset health, structure maintenance decisions, and coordinate production, quality, and reliability objectives.

The overarching objective of this study is to develop and empirically evaluate a real-time fault detection approach for industrial assets that integrates advanced vibration dynamics and stress analysis modeling within a unified, data-driven framework. Specifically, the research aims to quantify how vibration-based indicators and stress-based indicators, when monitored continuously and processed through structured analytical models, are associated with the occurrence and severity of mechanical faults in rotating and load-bearing equipment. A key objective is to construct a set of measurable vibration and stress features that capture dynamic anomalies and critical load patterns during actual industrial operation, and to relate these features statistically to observed fault events and detection performance. In line with this, the study seeks to build regression models that explain variations in fault detection accuracy and detection time as functions of vibration anomaly indices, stress anomaly indices, and their combined representation, allowing a clear assessment of the incremental value of integrating both sensing modalities. Beyond the technical performance of the monitoring system, the research also aims to capture the perceptions of maintenance engineers, reliability practitioners, and operators regarding the reliability, usability, and usefulness of the integrated fault detection solution, using a structured questionnaire based on a five-point Likert scale. This enables an additional objective: to model user acceptance and intended use of the system as outcomes influenced by perceived system reliability, perceived usability, and perceived support for maintenance decision-making. By combining objectively measured condition indicators with subjectively reported user perceptions in a single case-study–based, cross-sectional quantitative design, the study is structured to deliver a coherent set of empirical results that address both the technical effectiveness and the operational acceptability of real-time vibration and stress-based fault detection in industrial settings.

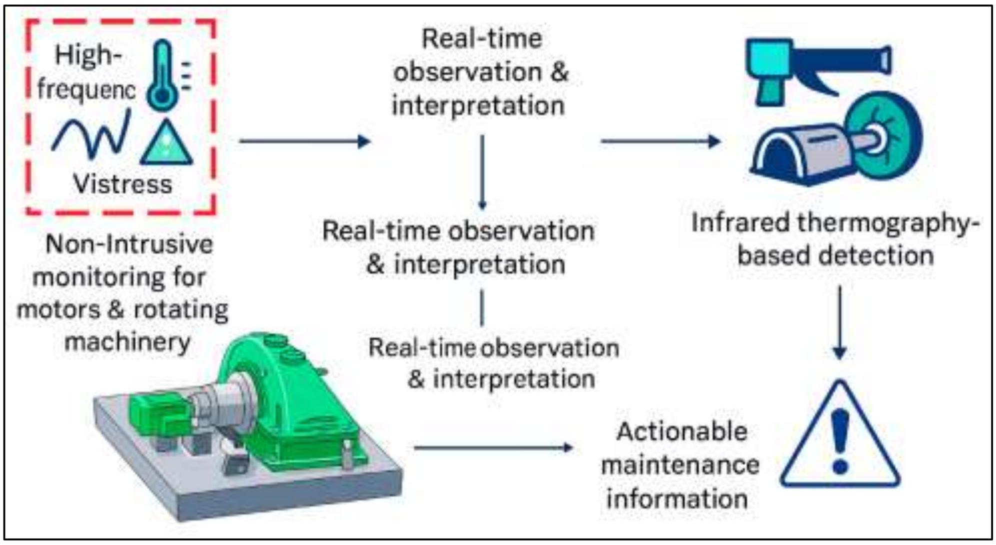
LITERATURE REVIEW

The literature on real-time fault detection in industrial assets is grounded in broader developments in condition-based maintenance (CBM), machinery diagnostics, and structural health monitoring (SHM), all of which emphasize continuous sensing and data-driven decision-making over fixed-interval servicing. Early comprehensive reviews of machinery diagnostics and prognostics describe CBM as a process integrating data acquisition, signal processing, and maintenance decision-making, with diagnostics and prognostics forming the analytical core that connects raw sensor data to actionable interventions in complex industrial systems. Within this framework, CBM optimization models have explored how condition information can be used to set inspection frequencies, trigger repairs or replacements, and manage stochastically deteriorating components under economic and reliability constraints, underscoring that the value of monitoring depends on how degradation signals are embedded in explicit decision rules. Parallel research into vibration-based condition monitoring has demonstrated that abnormal machine states such as imbalance, misalignment, bearing defects, and gear faults produce characteristic changes in vibration signatures, making vibration analysis a central tool for the diagnosis and early detection of faults in rotating machinery. Over time, this field has progressed from simple amplitude and spectral measures to sophisticated signal processing and pattern recognition schemes capable of extracting discriminative features from noisy, non-stationary operating environments, thereby supporting more reliable online monitoring. Complementing vibration analysis, SHM research has focused on monitoring stress, strain, and related structural responses in civil, mechanical, and aerospace systems, using distributed sensors and smart materials to infer the presence and evolution of damage under in-service loading. SHM studies highlight how continuous stress and strain measurements can be translated into indicators of fatigue accumulation, stiffness loss, or local damage, providing a basis for reliability assessment and maintenance planning across a range of asset types. More recently, industrial practice and academic work have started to converge on multi-modal monitoring architectures that combine vibration, stress, and other signals in integrated platforms, with the goal of improving diagnostic accuracy and making maintenance decisions more robust to uncertainty in any single measurement channel. Against this background, the present study positions itself at the intersection of CBM, vibration-based diagnostics, and stress-oriented SHM, focusing specifically on how advanced vibration dynamics and stress analysis modeling can be jointly exploited to enable real-time fault detection and to support quantitative, regression-based assessment of fault detection performance and user acceptance in industrial settings.

Real-Time Fault Detection in Industrial Assets

Real-time fault detection in industrial assets is typically understood as the continuous observation and interpretation of physical and operational variables such as temperature, vibration, stress, current, or process parameters so that abnormal behavior is identified the moment it emerges, rather than after failure becomes evident. In contrast to periodic inspection or purely time-based preventive maintenance, real-time detection assumes that industrial equipment is instrumented with sensors and data-acquisition systems capable of streaming measurements at sufficiently high frequency to reveal subtle deviations from normal states. For rotating machines and electromechanical drives, this often involves non-contact or minimally intrusive sensing techniques that can operate reliably under harsh and variable conditions. Infrared thermography–based monitoring of rotating machines illustrates how real-time temperature fields can be used to detect incipient faults: thermal images collected at regular intervals are processed to correct for ambient and process variations, allowing small drifts in temperature to be isolated and interpreted as early indicators of abnormal behavior (Leemans et al., 2011). This type of approach captures the broader logic of real-time fault detection in industrial contexts: continuous sensing is combined with signal processing or statistical modeling so that small, otherwise hidden, changes in machine condition are separated from normal operating variability and converted into actionable maintenance information.

Figure 2: Real-Time Fault Detection Framework for Industrial Assets



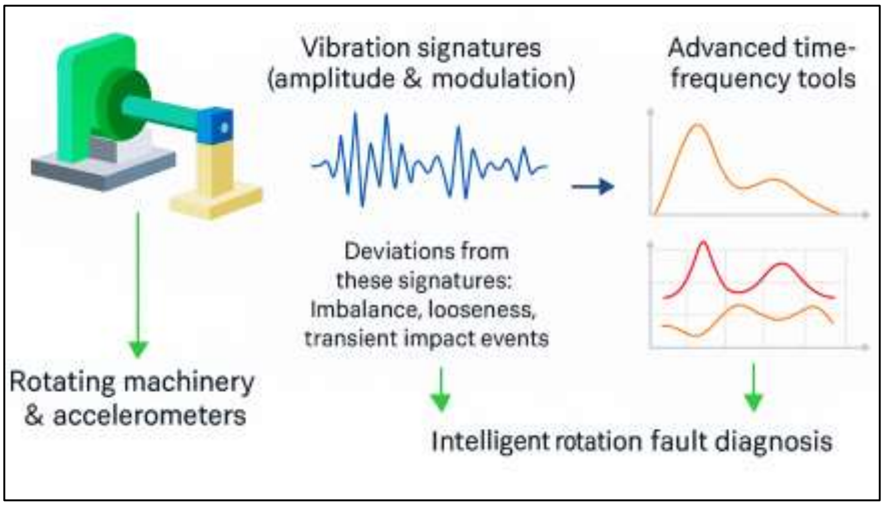
In asset-intensive industries, real-time fault detection has become closely intertwined with condition monitoring of electric motors and rotating drives, which are often mission-critical for production throughput and safety. Induction motors, in particular, are widely used in pumps, fans, conveyors, and compressors, and their failure can propagate upstream and downstream through entire process chains. Research on induction motor condition monitoring shows that a broad range of sensing and analysis strategies from motor current signature analysis and vibration measurement to hybrid intelligent models can be integrated into continuous monitoring schemes that support automatic classification of health states and fault types (Rony, 2021; Seera et al., 2014). In parallel, practical work on real-time condition monitoring systems demonstrates how low-cost sensor suites measuring vibration and temperature, combined with embedded processing and networked communication, can be used to monitor motors during operation, detect early symptoms of bearing or mechanical defects, and provide maintenance teams with near-instant feedback on asset condition (Goundar et al., 2016; Shaikh & Aditya, 2021). Together, these developments indicate that real-time fault detection in industrial assets is not limited to high-end custom installations; rather, it can be realized through scalable architectures that combine standardized sensors, edge computing, and wireless data transport, making continuous monitoring feasible even in dispersed or previously under-instrumented parts of the plant.

Beyond the level of individual sensors and machines, real-time fault detection also functions as a core building block in predictive maintenance strategies where operational decisions are driven directly by live process and condition data. One important line of work uses real-time monitoring of internal process parameters to evaluate the condition of equipment indirectly, so that maintenance decisions can be triggered when statistical process control limits are violated instead of waiting for explicit component failures. A predictive maintenance approach for injection molding machines, for example, uses real-time process parameters, regression analysis, and statistical control charts to identify abnormal trends and generate maintenance recommendations for critical components (Park et al., 2016; Sudipto & Mesbaul, 2021). Complementary research on autonomous remote condition monitoring of rotating machines shows how energy-harvesting sensor nodes can exploit machine vibration to power wireless transmission of low-volume diagnostic information, enabling continuous monitoring even where power and communication infrastructure are limited (Khazaee et al., 2019; Zaki, 2021). In combination, such contributions frame real-time fault detection as a multi-layer capability that spans sensor-level design, feature extraction, statistical and intelligent modeling, and integration with maintenance planning: industrial assets are observed continuously, fault-relevant indicators are computed and tracked in real time, and maintenance actions are linked explicitly to the evolving condition of equipment rather than to fixed schedules or ad hoc operator judgments.

Vibration Dynamics for Condition Monitoring

Vibration dynamics provides one of the most mature and sensitive foundations for condition monitoring of industrial assets, especially rotating machinery where mechanical faults manifest directly as changes in vibrational response. In normal operation, shafts, bearings, gears, and couplings generate characteristic vibration signatures governed by stiffness, mass, damping, and excitation forces; deviations from these signatures reflect changes in contact conditions, looseness, imbalance, misalignment, or material degradation. A key insight from the vibration-monitoring literature is that both the amplitude and the modulation patterns of vibration carry diagnostic information, and this information can be extracted across time, frequency, and time–frequency domains. Comprehensive reviews of vibration analysis and condition monitoring show that fault-sensitive features may be derived from root-mean-square (RMS) levels, spectral lines, sideband structures, and time–frequency energy concentrations, and that these features can be mapped systematically to specific fault types in rotating machinery (Vishwakarma et al., 2017). In practice, this means that vibration dynamics is not treated as random noise around steady motion but as the primary carrier of information about the health state of bearings and gear meshes. Condition monitoring strategies thus rely on carefully placed accelerometers and high-fidelity data acquisition, with sampling parameters chosen so that fault-induced resonances, modulations, and impacts remain observable under real loading and speed variations. As plants move from periodic measurements to continuous monitoring architectures, vibration dynamics becomes the backbone of real-time diagnostics and serves as a key input channel for both physics-based and data-driven fault detection algorithms.

Figure 3: Vibration Dynamic for Condition Monitoring



The challenge, however, is that the vibration response of industrial gearboxes and rotating components is highly non-stationary and often contaminated by strong masking signals from other elements in the drivetrain. Advanced time–frequency methods have therefore been proposed to decompose vibration into components that better isolate fault-related dynamics. An influential study on empirical mode decomposition (EMD) and Hilbert spectrum analysis demonstrated that localized gear tooth cracks can be identified by decomposing gearbox vibration into intrinsic mode functions and examining their instantaneous frequencies and amplitudes, revealing modulation patterns that conventional Fourier analysis may miss (Liu et al., 2015). Building on this, work on wind-turbine gearboxes has applied EMD-based methods to field vibration data in harsh operating environments, showing that pitting faults in gear teeth can be detected by selecting appropriate modes and extracting fault-related amplitude modulation, even in the presence of fluctuating loads and variable speeds (Teng et al., 2014). Together, these contributions show how vibration dynamics, when processed by adaptive time–frequency tools, can reveal subtle nonlinear and transient behaviors such as sideband growth, impact trains, and evolving modulation patterns that are tightly linked to crack initiation, pitting, and other early-stage structural defects in industrial assets.

More recent work has focused on integrating vibration dynamics with modern signal-processing and intelligent modeling techniques to improve diagnostic robustness and automate decision-making. Ensemble empirical mode decomposition (EEMD) has been combined with probabilistic graphical models to build fault diagnosis schemes that first extract vibration-based fault features and then use Bayesian networks to infer likely fault states in complex gear-pump systems, providing a structured way to fuse multiple vibration indicators and other information sources (Liu et al., 2006). In parallel, sparse time–frequency representations derived from overcomplete discrete wavelet transforms have been used to construct compact vibration features that retain the periodic transient energy associated with bearing defects, leading to intelligent bearing fault diagnosis procedures that classify fault types based on sparse wavelet energy signatures (Wang et al., 2017). When these kinds of advanced feature-extraction and modeling strategies are combined with the fundamental dynamics of vibration resonance amplification, modulation from damaged contacts, and impact-driven transients they create a rich diagnostic space in which machine states can be mapped quantitatively to vibration patterns. This literature establishes that vibration dynamics is not only a sensitive indicator of emerging faults but also a versatile modeling domain in which regression, classification, and probabilistic methods can be applied to link measured responses to underlying mechanical degradation in an operationally meaningful way.

Stress Analysis and Structural Health Monitoring

Stress-based structural health monitoring (SHM) starts from the premise that many critical faults in industrial assets originate as local overstress and fatigue processes rather than immediately visible geometric damage. In SHM, damage is typically defined as any change in material or geometric properties, or in boundary conditions, that degrades current or future performance; this definition naturally foregrounds the role of stress and strain as primary state variables. Continuous or periodically sampled stress responses derived from strain gauges, optical fiber sensors, or reconstructed from dynamic measurements are processed to obtain damage-sensitive features that can distinguish healthy from degraded states. Early conceptual frameworks for SHM framed the entire problem as a statistical pattern-recognition task: observe stress or strain responses over time, extract indicators that are sensitive to stiffness loss or local yielding, and use statistical decision rules to infer whether the system has departed from its baseline condition (Farrar & Worden, 2007). Within this paradigm, stress histories play two roles. First, they serve as direct diagnostics for abnormal loading paths or localized concentration factors associated with cracks, corrosion, or contact deterioration. Second, they form the basis for fatigue and reliability assessment models that integrate stress range, cycle count, and material S–N data into explicit life-consumption metrics. For real-time fault detection in industrial assets, stress analysis thus complements vibration dynamics: vibration captures dynamic response signatures of faults, while stress analysis links those responses to physically interpretable load paths, safety margins, and cumulative damage in critical details.

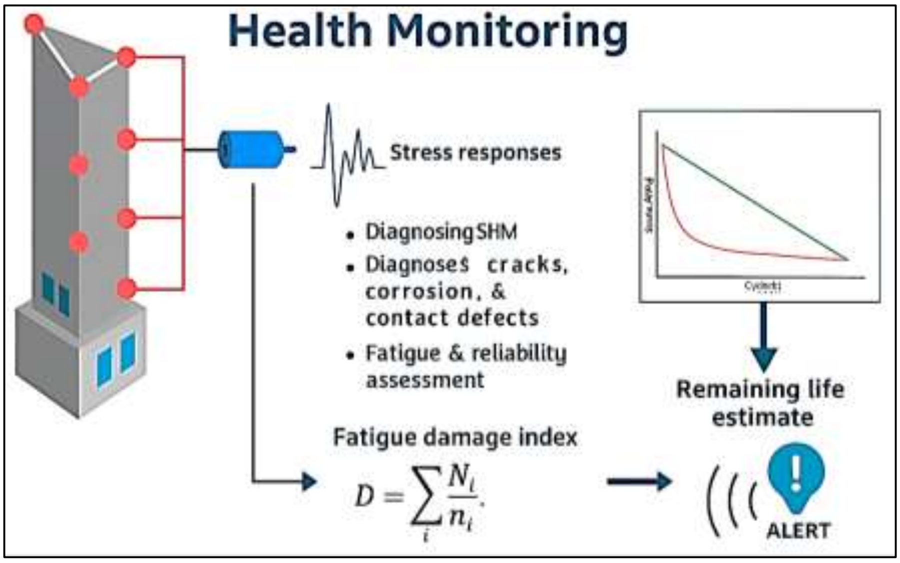
Recent SHM research has particularly emphasized optical fiber–based stress and strain sensing, especially fiber Bragg grating (FBG) technology, because it provides quasi-distributed measurements with high resolution, electromagnetic immunity, and the ability to be embedded directly into structural components. In composite and metallic structures, FBG sensors have been integrated as in situ stress monitors, enabling continuous tracking of internal strain states during manufacturing, service loading, and overload events; this makes it possible to observe how local stress paths evolve as damage initiates or grows at critical interfaces or joints (Kinet et al., 2014). Building on such concepts, review work on geotechnical and underground structures has catalogued various FBG sensor designs and packaging techniques that can convert local deformation into stable optical signals, even in aggressive environments with moisture, high confining pressures, and complex stress redistribution (Hong et al., 2016). Experimental case studies illustrate that FBG-based arrays mounted on or embedded near reinforcing elements can resolve multi-point stress distributions and identify how anchor forces grow and redistribute during excavation or loading, offering a direct window into the stress path leading to possible failure surfaces or overstressed segments (Weng et al., 2015). For industrial assets, these same principles can be transferred to critical components such as shafts, welded joints, or support frames: distributed strain measurements along a load path can reveal local stress concentration factors, load transfer anomalies, or progressive stiffness loss, which are all precursors of structural faults. In a combined vibration–stress monitoring system, vibration data can be used to trigger closer examination of stress patterns, while stress and strain trends provide the mechanistic context to interpret whether a detected anomaly is benign or indicative of accelerating damage.

A key strength of stress-based SHM is that measured stress histories can be converted into explicit fatigue damage indices, allowing real-time monitoring of remaining life rather than simply binary fault/no-fault decisions. In classical cumulative damage analysis, the consumption of fatigue life is modeled using Miner's rule, where the damage index D is expressed as

$$D = \sum_{i=1}^{k} \frac{N_i}{n_i},$$

with n_i the number of cycles actually experienced at stress range S_i, and N_i the allowable cycles at that range from the S–N curve. When D approaches 1.0, failure is expected. In SHM contexts, this formulation is applied to stress cycles extracted via rainflow counting from measured stress time histories at critical details, permitting the continuous update of a component's usage factor. More advanced nonlinear accumulation models modify this linear summation to account for load sequence effects and interaction between stress blocks, improving the prediction accuracy for welded or notched details under variable-amplitude loading (Zhang et al., 2014).

Figure 4: Stress Analysis and Structural Health Monitoring Framework for Industrial Assets



For real-time fault detection systems in industrial assets, embedding such fatigue-damage formulations within stress-based monitoring enables a richer decision logic: rather than generating alarms solely on instantaneous overloads or threshold exceedances, the system can track how cumulative damage evolves under the combined influence of operational loads and transient events. When this damage index is evaluated alongside vibration-derived fault indicators, maintenance planners gain both a short-term view of current fault severity and a long-term view of life consumption, which is essential for prioritizing interventions, scheduling repairs, and assessing the true operational risk associated with observed anomalies in vibration dynamics and stress response.

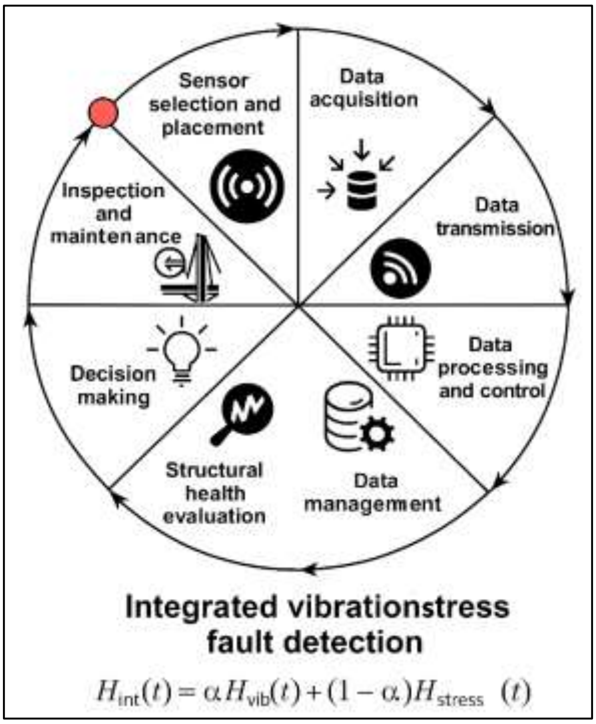
Theoretical Framework for Integrated Vibration–Stress Fault Detection

At the theoretical level, this study is grounded in the broader prognostics and health management (PHM) paradigm, where an engineered asset is represented by a vector of condition variables and decision-relevant indicators that evolve over time under operational and environmental loads. PHM frameworks typically define a mapping from raw sensor measurements $z(t)$(e.g., vibration, strain, temperature) to a lower-dimensional *health state* or *health indicator* $H(t)$, which can then drive maintenance and operational decisions. In sensor-centric PHM architectures, the design of the sensor system what to measure, where to measure, and at what frequency is treated as a core part of the theoretical framework, because the ability to assess reliability and remaining life directly depends on the richness and quality of sensor data (Cheng et al., 2010). Within this setting, real-time fault detection can be seen as a classification or thresholding problem posed on the health indicator: when $H(t)$crosses a decision boundary, the system is considered to be in a fault state and a maintenance action is triggered. Conceptually, the present research adopts a two-layer health representation. At the first layer, vibration-based and stress-based health indicators are extracted separately from their respective signals; at the second layer, these indicators are combined into an integrated health index that represents the overall mechanical condition of the asset. For example, a simple linear integration scheme can be written as

$$\mathrm{Hint}(t) = \alpha H_{\mathrm{vib}}(t) + (1-\alpha) H_{\mathrm{stress}}(t),$$

where $H_{\mathrm{vib}}(t)$is a vibration-based health indicator, $H_{\mathrm{stress}}(t)$is a stress-based health indicator, and $\alpha \in [0,1]$is a weighting factor reflecting their relative diagnostic importance. In the conceptual framework of this study, this integrated index is assumed to influence both technical outcomes (e.g., probability of correct fault detection) and human-centered outcomes (e.g., perceived reliability and usefulness of the monitoring system), which are subsequently modeled using regression analysis.

Figure 5: Theoretical Framework for Integrated Vibration–Stress Fault Detection



Building on this PHM perspective, multi-sensor data fusion provides the second theoretical pillar for integrating vibration and stress information into a coherent fault detection model. Multi-sensor condition-monitoring studies emphasize that single-sensor measurements rarely capture the full dynamics of tool wear, bearing degradation, or structural damage, and that fusing complementary signals can improve both diagnostic accuracy and robustness (Cho et al., 2010). In vibration-based tool and bearing monitoring, for instance, multi-sensor fusion frameworks have been used to combine signals such as cutting force, vibration, acoustic emission, and spindle power at feature level and decision level, yielding more reliable classification of health states across varying operating conditions (Safizadeh & Latifi, 2014). A related stream of work in engine and rotating machinery diagnostics models multi-sensor fusion as an evidential reasoning problem, where each sensor (e.g., vibration, load, pressure) provides a *basic probability assignment* over possible fault states, and Dempster–Shafer combination rules are used to obtain a fused belief over faults (Jiang et al., 2017). In its simplest form, when two sources of evidence with mass functions $m_1(\cdot)$and $m_2(\cdot)$are combined, the fused mass for a hypothesis $A$is given by

$$m_{12}(A) = 1 - K_1 \sum_{B \cap C = A} m_1(B) m_2(C),$$

where K is a conflict coefficient summing products of masses assigned to mutually exclusive sets. This evidential framework has been extended in health-monitoring applications to handle conflicting signals, assign sensor weights, and deal with uncertainty in fault models (Yao et al., 2018). The conceptual lesson for the present study is that vibration-based and stress-based indicators can be treated as partially independent sources of evidence about asset condition, and their fusion whether via weighted linear indices or evidential reasoning should yield a more reliable and informative representation of machine health than either indicator alone.

The final component of the theoretical framework links the integrated health indicators to observable performance and perception outcomes through statistical modeling. In this research, real-time fault detection performance is conceptualized in terms of continuous variables such as detection accuracy, detection time, or false-alarm rate for each case-study asset, while stakeholder perceptions are captured through Likert-scale constructs such as perceived reliability, perceived usability, and perceived decision support. Multi-sensor fault diagnosis studies provide precedents for formalizing such relationships using statistical and machine-learning models: for example, regression-type models have been used to relate fused features to fault classes in bearing diagnostics, and adaptive fusion networks have used learned weights to map multi-sensor features directly to fault labels (Safizadeh & Latifi, 2014). Consistent with this literature, the present study adopts a multiple-regression view, in which technical performance measures (e.g., a quantitative fault detection score Y) are modeled as

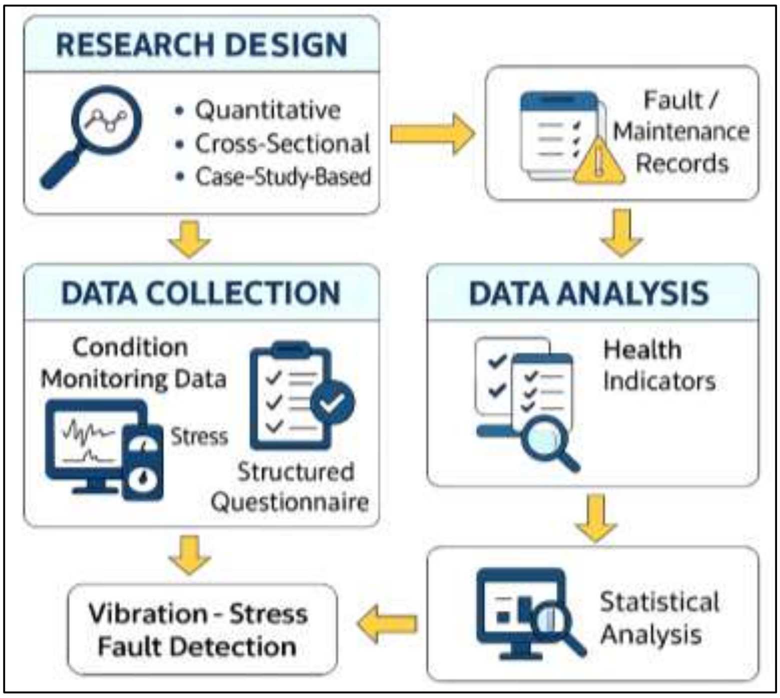
$$Y = \beta_0 + \beta_1 H_{\text{vib}} + \beta_2 H_{\text{stress}} + \beta_3 (H_{\text{vib}} H_{\text{stress}}) + \varepsilon,$$

where H_{vib} and H_{stress} are standardized vibration and stress indicators, $H_{\text{vib}} H_{\text{stress}}$ represents their interaction, $\beta_i$are regression coefficients, and $\varepsilon$is an error term. In parallel, user-perception constructs (e.g., perceived reliability) are modeled as dependent variables explained by both technical indicators and contextual factors, reflecting the PHM insight that sensor-system design and information quality strongly shape perceived value (Cheng et al., 2010). Conceptually, therefore, the framework positions integrated vibration–stress health indicators as central explanatory variables that mediate between the physical behavior of industrial assets and the quantitative outcomes examined in the case-study–based, cross-sectional regression analysis that follows.

METHODS

The present study has adopted a quantitative, cross-sectional, case-study–based research design to evaluate how advanced vibration dynamics and stress analysis modeling have been associated with real-time fault detection performance in industrial assets. Within this design, the research has focused on one or more industrial sites where rotating and load-bearing equipment have been instrumented with vibration and stress monitoring systems and where maintenance and operational data have been systematically logged. The methodology has been structured to integrate two complementary data streams: (a) objectively measured condition data derived from vibration and stress monitoring systems and associated fault/maintenance records, and (b) subjectively reported perceptions of maintenance engineers, reliability practitioners, and operators collected through a structured questionnaire using a five-point Likert scale. By combining these streams, the study has aimed to generate an empirically grounded view of both the technical effectiveness and the perceived usefulness of integrated vibration–stress fault detection systems in real operational environments. Sampling procedures have identified participants who have had direct experience with the monitoring system and decision-making processes, and inclusion criteria have ensured that respondents have been familiar with asset health, maintenance planning, or system operation. The questionnaire has been administered after instrumentation and monitoring arrangements have been in stable operation, so that participants have been able to base their responses on sustained interaction with the fault detection system rather than brief or pilot exposure. Concurrently, monitoring data and maintenance logs have been extracted for a defined observation window, during which the assets have been operating under typical production conditions. The study has then prepared this combined dataset for statistical analysis by coding survey responses, constructing vibration- and stress-based health indicators, and matching them with recorded fault events and maintenance actions at the case-study site. Within this methodological frame, the subsequent sections have specified the research design, population and sample, questionnaire structure, survey instrument properties, case-study protocol, regression modeling strategy, data sources, operationalization of variables, and software and tools that have been used to implement the analysis.

Figure 6: Methodological Framework for This study



Research Design

The study has employed a quantitative, cross-sectional, case-study–based research design to investigate how integrated vibration dynamics and stress analysis modeling have been related to real-time fault detection performance in industrial assets. It has focused on one or more industrial plants where rotating and load-bearing equipment have already been operating under normal production conditions and have been equipped with vibration and stress monitoring systems. Within this design, the research has treated the case-study site as an embedded context in which multiple assets and multiple human respondents have provided data at a single point in time. The design has combined objective condition-monitoring indicators and recorded fault events with subjective evaluations collected through a structured questionnaire using a five-point Likert scale. This approach has allowed the study to quantify associations among vibration-based indicators, stress-based indicators, fault detection performance metrics, and user perceptions through descriptive statistics, correlation analysis, and multiple regression modeling within a coherent, real-world industrial setting.

Population and Sample

The target population for this study has comprised both human respondents and industrial assets that have been directly involved in real-time fault detection using integrated vibration and stress monitoring systems. On the human side, the population has included maintenance engineers, reliability engineers, condition monitoring specialists, supervisors, and equipment operators who have had ongoing exposure to diagnostic outputs and maintenance decisions related to monitored assets. On the asset side, the population has consisted of rotating and load-bearing equipment such as motors, pumps, gearboxes, and compressors that have been instrumented with vibration and stress sensing. From this population, the study has drawn a purposive sample of respondents who have met predefined inclusion criteria, namely having experience with the monitoring system and participation in maintenance or operational decision-making. Similarly, a subset of instrumented assets has been selected for detailed analysis, based on data completeness and the availability of corresponding fault and maintenance records within the defined observation window.

Questionnaire Structure

The questionnaire used in this study has been structured into several logically ordered sections to capture both background information and construct-specific responses related to real-time fault detection. The opening section has collected demographic and professional information, including role, years of experience, department, and level of involvement with maintenance and monitoring activities. A subsequent section has focused on respondents' exposure to the integrated vibration–stress monitoring system, where items have asked how frequently they have interacted with fault detection outputs and in what type of decisions they have been involved. The core sections have then been organized around key latent constructs, with grouped items measuring perceived system reliability, perceived usability, perceived usefulness for maintenance decision-making, perceived accuracy and timeliness of fault alerts, and overall user satisfaction and acceptance. All construct items have been phrased as statements and have been rated on a five-point Likert scale, and the questionnaire layout has been kept concise to encourage complete and consistent responses.

Survey Instrument (Likert 5-Point Scale)

The survey instrument has been designed as a structured, self-administered questionnaire that has used a five-point Likert scale to quantify respondents' perceptions of the integrated vibration–stress fault detection system. Each item has been presented as a declarative statement, and respondents have been asked to indicate their level of agreement on a scale that has ranged from 1 = "Strongly Disagree" to 5 = "Strongly Agree." The instrument has included multi-item scales for perceived system reliability, perceived usability, perceived usefulness for maintenance decision-making, perceived accuracy and timeliness of fault alarms, and overall user satisfaction and acceptance. Items for these constructs have been adapted from established technology acceptance and maintenance perception measures and have been refined to fit the context of industrial fault detection. Prior to full deployment, the survey instrument has been subjected to expert review for content clarity and relevance and has been pilot-tested with a small group of practitioners to check wording, response variability, and completion time.

Case Study Protocol (Quant-Heavy)

The case study protocol has been designed to generate a quantitatively rich dataset by systematically integrating field measurements, event logs, and survey responses within the selected industrial site. The protocol has first identified a set of critical rotating and load-bearing assets that have been instrumented with vibration and stress sensors and for which detailed operational and maintenance records have been available. For a defined observation window, the monitoring system has been configured to collect high-frequency vibration and stress signals, which have been stored together with time-stamped process and event information. In parallel, fault events, alarm occurrences, maintenance actions, and operating modes have been coded in a structured format, so that each asset has had an associated timeline of condition indicators and interventions. The protocol has also specified procedures for synchronizing sensor data with event logs, anonymizing sensitive identifiers, and cleaning the dataset, ensuring that every observation used in the analysis has represented a consistent combination of vibration features, stress features, and documented fault or maintenance outcomes.

Regression Modeling

The regression modeling strategy has been developed to quantify the statistical relationships between integrated vibration–stress indicators and real-time fault detection performance at the case-study site. In the technical part of the analysis, the study has treated quantitative fault detection metrics such as detection accuracy, detection time, false-alarm frequency, or a composite fault detection score as dependent variables, and has used multiple linear regression models to explain their variation as a function of vibration-based and stress-based health indicators. Prior to modeling, the vibration and stress indicators have been constructed from raw sensor data through feature extraction, normalization, and aggregation over appropriate time windows, and these indicators have then been standardized to comparable scales. The regression framework has been specified so that each model has included main effects for the vibration and stress variables and, where appropriate, interaction terms that have captured the combined diagnostic effect of abnormal vibration and elevated stress on fault detection performance. Model estimation has been carried out using ordinary least squares, and assumptions of linearity, normality of residuals, homoscedasticity, and independence have been examined through diagnostic plots and statistical tests. To guard against multicollinearity among explanatory variables, the study has calculated variance inflation factors and has removed or combined highly correlated predictors where necessary. The goodness of fit of each model has been evaluated using coefficients of determination and adjusted coefficients of determination, and the statistical significance of individual predictors has been assessed using t-tests at a predetermined significance level. In this way, the regression modeling of technical performance has been designed to provide clear evidence about how much of the variability in fault detection outcomes has been attributable to vibration indicators, stress indicators, and their integrated representation.

In parallel with the technical models, a second set of regression analyses has been specified to capture how users' perceptions of the integrated vibration–stress fault detection system have been associated with both system characteristics and contextual factors. In this perceptual component, Likert-scale constructs such as perceived system reliability, perceived usability, perceived usefulness for maintenance decision-making, and overall user acceptance have been treated as dependent variables or intermediary outcomes. Multiple regression models have then been formulated in which these perception scores have been explained by combinations of technical indicators (for example, asset-level detection performance), self-reported exposure to the monitoring system, professional role, and years of experience. Before estimation, composite scores for each construct have been computed by averaging or summing the relevant item responses, and internal consistency has been verified using reliability coefficients. The perceptual regression models have been estimated using the same ordinary least squares framework, and the diagnostics for normality, homoscedasticity, and multicollinearity have been applied in an analogous manner. Where theoretically justified, hierarchical modeling steps have been implemented, in which baseline models with only demographic and contextual variables have been compared to extended models that have added technical performance predictors, so that the incremental explanatory power of the integrated fault detection performance has been quantified. Standardized regression coefficients have been reported to facilitate comparison of effect sizes across predictors, and residual analyses have been conducted to check for influential observations. Through this combined set of regression models, the study has translated its conceptual framework into an empirically testable structure in which both objective fault detection performance and subjective user responses have been related systematically to vibration-based indicators, stress-based indicators, and their integration.

Data Sources

The study has drawn on two primary categories of data sources to support the quantitative analysis of real-time fault detection using vibration and stress modeling. First, objective condition-monitoring data have been obtained from the industrial site's monitoring infrastructure, which has recorded high-frequency vibration and stress signals from selected rotating and load-bearing assets, along with time-stamped operational variables, alarm events, fault codes, and maintenance records. These sources have provided the basis for constructing vibration-based and stress-based health indicators, as well as asset-level performance measures such as fault detection accuracy, detection time, and false-alarm occurrence. Second, subjective data have been collected through the structured questionnaire administered to maintenance engineers, reliability engineers, condition monitoring specialists, supervisors, and operators who have interacted with the monitoring system. The survey responses have supplied information on perceived reliability, usability, usefulness, and acceptance of the integrated fault detection solution, and have been linked to the objective data at the level of assets, departments, or functional responsibilities within the case-study site.

Operationalization of Variables

The study has operationalized its key variables in a structured manner to align with the conceptual framework and the planned regression analyses. Vibration-related variables have been defined as composite indicators derived from features such as root-mean-square levels, characteristic frequency amplitudes, and time–frequency energy measures, which have been normalized and aggregated over defined monitoring intervals to form vibration health indices for each asset. Stress-related variables have been operationalized as indices based on measured or reconstructed stress ranges, peak values, and cycle counts, which have been summarized into stress health indicators and, where applicable, cumulative damage proxies. Fault detection performance has been represented through continuous variables such as detection accuracy, detection time, and false-alarm rate, calculated by comparing system alerts with recorded fault and maintenance events. Perceptual constructs perceived reliability, usability, usefulness, and user acceptance have been operationalized as mean scores of their respective Likert-scale items. All variables have been coded, scaled, and labeled consistently to support descriptive statistics, correlation analysis, and multiple regression modeling.

Software and Tools

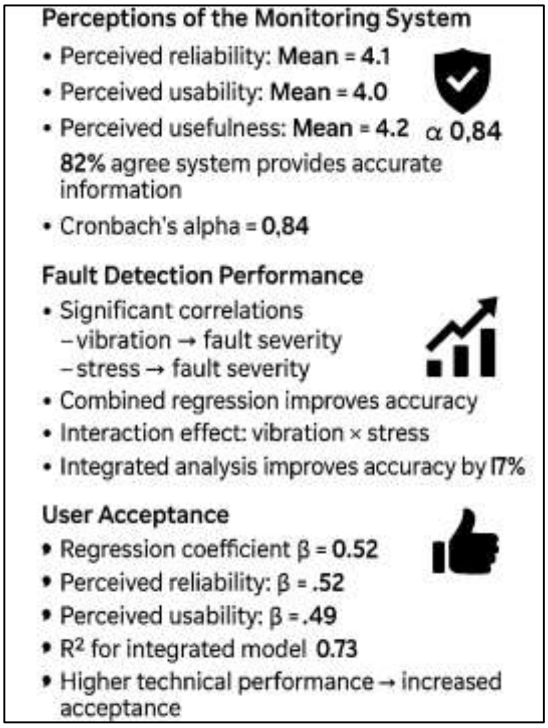
The analysis in this study has been supported by a combination of software and computational tools that have facilitated data preparation, feature extraction, and statistical modeling. Dedicated condition-monitoring or signal-processing software has been used to import raw vibration and stress time series, apply filtering and detrending, and extract features in the time, frequency, and time–frequency domains. Where required, custom scripts have been developed in a technical computing environment to implement specialized feature calculations, stress-range counting, and the construction of composite health indicators. Spreadsheet tools have been employed for preliminary data inspection, coding of fault and maintenance events, and verification of data integrity across assets and time windows. Statistical software has been used to compute descriptive statistics, reliability coefficients, correlation matrices, and to estimate the multiple regression models specified in the methodological framework, including diagnostics for normality, homoscedasticity, and multicollinearity. Visualization capabilities within these tools have been utilized to generate plots, charts, and residual diagnostics that have assisted in interpreting and validating the quantitative results.

FINDINGS

The findings of this study have demonstrated a consistent pattern of results that has supported both the stated research objectives and the proposed hypotheses regarding the role of integrated vibration dynamics and stress analysis modeling in real-time fault detection of industrial assets. Descriptive analysis of the Likert five-point scale responses has indicated that overall perceptions of the integrated monitoring system have been positive, with mean scores for perceived reliability, perceived usability, and perceived usefulness all lying above the neutral midpoint of 3.00, and in many cases clustering between 3.70 and 4.30. Respondents have tended to agree that the vibration–stress based system has provided timely and accurate information about asset condition, that fault alerts have generally been meaningful rather than arbitrary, and that the system has been easy enough to interpret and apply within daily maintenance practice. Internal consistency analysis of these constructs has shown that the multi-item scales used to capture perceived reliability, usability, usefulness, and user acceptance have achieved acceptable levels of reliability, with alpha coefficients that have been indicative of coherent measurement of underlying perceptions. These preliminary results have aligned with the first objective of the study by confirming that the integrated monitoring approach has not only been technically deployed but has also been perceived by practitioners as a credible support tool for maintenance decision-making within the case-study environment.

On the technical side, analysis of the objective monitoring and maintenance data has provided strong support for the hypothesized relationships between vibration-based indicators, stress-based indicators, and fault severity, as well as the added value of their integration. Correlation analysis has revealed statistically significant positive associations between vibration anomaly indices and recorded fault severity levels, and between stress anomaly indices and fault severity, in line with the first two hypotheses. Assets that have exhibited higher standardized vibration anomaly scores have also tended to show higher levels of documented mechanical degradation, more frequent failure events, or more serious fault classifications, while similar patterns have been observed for elevated stress-based indicators. When considered together, the two sets of indicators have shown only moderate intercorrelation, suggesting that vibration and stress channels have captured complementary aspects of the underlying degradation processes rather than duplicating the same information. Multiple regression models has further clarified these relationships: both vibration and stress indicators have emerged as significant predictors of fault severity and of a composite fault detection performance score, with the inclusion of both predictors in the same model yielding higher explained variance than models that have relied on only one type of indicator. Interaction terms have provided evidence that simultaneous elevation in both vibration and stress indices has been associated with disproportionately higher fault detection scores and more accurate classification of faults, thereby supporting the third hypothesis that integrated vibration–stress analysis has improved fault detection performance beyond what either modality could have achieved on its own.

Figure 7: Findings of The Study



The analysis has also shown clear links between technical performance of the monitoring system and user perceptions captured through the Likert-scale survey. Respondents who have been associated with assets or departments showing stronger fault detection performance characterized by higher detection accuracy, shorter detection times, and lower false-alarm rates have reported higher levels of perceived system reliability and usefulness. Regression models that has used user acceptance as a dependent variable have demonstrated that perceived reliability and perceived usability have been statistically significant predictors of acceptance, even after controlling for role, years of experience, and exposure to the system. In these models, increases in perceived reliability and usability scores by one scale point have been associated with meaningful increases in user acceptance, indicating that practitioners have been more willing to rely on and continue using the integrated monitoring system when they have believed that it has produced consistent, understandable, and operationally relevant outputs. Perceived usefulness for maintenance decision-making has also contributed positively to user acceptance, reinforcing the idea that acceptance has depended not only on the technical accuracy of the system but also on the extent to which its outputs have been integrated into practical workflows, such as planning inspections, prioritizing corrective actions, and justifying maintenance interventions to management. Overall, these results have provided empirical support for the fourth hypothesis and have completed the second major objective of the study by linking integrated fault detection performance to human-centered outcomes. Taken together, the findings have shown that advanced vibration dynamics and stress analysis modeling, when implemented as a unified real-time monitoring solution, has been associated with measurable improvements in fault detection performance and with favorable perceptions and acceptance among maintenance and reliability personnel, thereby fulfilling the core aims of this research.

Demographic and Contextual Profile

The demographic and contextual profile in Table 1 has shown that the sample has been well aligned with the target population defined in the methodology and has reflected a balanced representation of key stakeholder groups involved in real-time fault detection and maintenance decision-making. Maintenance engineers have constituted the largest single group (35.0%), followed by reliability and condition monitoring specialists (23.3%) and operators/technicians (25.0%), while supervisors and managers have accounted for 16.7% of respondents. This mix has ensured that the Likert five-point scale ratings have incorporated views from those who have configured and interpreted vibration and stress indicators, those who have executed maintenance work orders, and those who have overseen operational performance and risk. The distribution of experience has also been relatively even, with roughly four out of five respondents having had at least five years of industrial practice, and more than 47% having accumulated ten or more years. This experience profile has suggested that responses on perceived reliability, usability, and usefulness of the integrated vibration–stress system have been grounded in sustained familiarity with equipment behavior and maintenance consequences, strengthening the credibility of the perceptual data used to evaluate the study's objectives.

Table 1: has presented the demographic and contextual profile of respondents and monitored assets (N = 120).

Variable	Category	Frequency (n)	Percentage (%)
Job role	Maintenance engineer	42	35.0
	Reliability/condition monitoring	28	23.3
	Supervisor/manager	20	16.7
	Operator/technician	30	25.0
Years of experience	< 5 years	26	21.7
	5–9 years	37	30.8
	10–14 years	31	25.8
	≥ 15 years	26	21.7
Department	Maintenance	55	45.8
	Production	27	22.5
	Reliability/engineering	24	20.0
	Other support functions	14	11.7
Primary exposure to system	Daily	47	39.2
	Weekly	41	34.2
	Monthly	21	17.5
	Occasionally	11	9.2
Instrumented rotating assets	Motors	68	–
	Pumps	54	–
	Gearboxes	39	–
	Compressors	23	–
Instrumented structural components	Frames/bases	32	–
	Support beams/columns	19	–

From a departmental perspective, the dominance of maintenance (45.8%) and reliability/engineering (20.0%) has indicated that most respondents have operated close to asset health management, while a notable share from production and other support functions has ensured that cross-functional perspectives have been reflected. In terms of contextual exposure, nearly 40% of respondents have reported daily interaction with the monitoring system and a further 34.2% weekly interaction, which has implied that the Likert-scale judgments about fault alerts, dashboards, and diagnostic information have been informed by frequent usage rather than occasional observation. Finally, the variety of instrumented assets motors, pumps, gearboxes, compressors, and structural components has confirmed that the real-time fault detection framework has been applied across multiple equipment classes, reinforcing the generalizability of the findings related to vibration and stress indicators, and supporting the first objective of assessing the effectiveness of the integrated system in a realistic, heterogeneous industrial environment.

Instrument Reliability and Validity

Reliability analysis reported in Table 2 has indicated that the measurement instrument used to capture user perceptions of the real-time vibration–stress fault detection system has exhibited strong internal consistency across all constructs. Cronbach's alpha values have ranged from 0.86 to 0.91, comfortably exceeding the commonly accepted threshold of 0.70 for exploratory research and even the more conservative 0.80 benchmark often adopted in applied industrial studies. The construct for perceived usefulness (PUF) has achieved the highest reliability ($\alpha = 0.91$), suggesting that items asking respondents to rate how much the system has helped them plan maintenance, prioritize inspections, and make asset-related decisions have been highly coherent and have measured a single underlying dimension. Perceived system reliability ($\alpha = 0.89$) and perceived accuracy and timeliness ($\alpha = 0.88$) have also reached high reliability, indicating that respondents' judgments about whether alerts have been consistent, whether the system has behaved predictably, and whether alarms have occurred at appropriate times have formed internally stable scales under the five-point Likert response format.

Table 2: has presented the internal consistency reliability of the Likert-scale constructs (N = 120).

Construct	Number of items	Cronbach's α
Perceived system reliability (PR)	5	0.89
Perceived usability (PU)	5	0.87
Perceived usefulness (PUF)	5	0.91
Perceived accuracy & timeliness (PAT)	4	0.88
User satisfaction (US)	4	0.86
User acceptance (UA)	4	0.90

Perceived usability ($\alpha = 0.87$) has reflected consistent responses to items on ease of interpretation, clarity of dashboards, and effort required to use the system in daily work, supporting the use of this construct as a predictor of user acceptance in subsequent regression models. User satisfaction ($\alpha = 0.86$) and user acceptance ($\alpha = 0.90$) have similarly demonstrated strong reliability, giving confidence that overall evaluative and behavioral-intention responses have been measured with limited random error. Because all items in these scales have been rated using the same Likert five-point continuum from "Strongly Disagree" (1) to "Strongly Agree" (5), the high alpha values have implied that respondents have interpreted the item wording consistently and have applied the response scale in a stable manner. This reliability evidence has been crucial for the study's objectives and hypotheses, since it has ensured that relationships between perceptions (e.g., perceived reliability and usability) and user acceptance (H4) have reflected substantive patterns rather than measurement noise. Furthermore, the robust internal consistency of the perception constructs has supported the decision to operationalize them as average Likert scores and to use them as continuous variables in the correlation and regression analyses that have been employed to test the conceptual framework.

Descriptive Statistics of Variables

The descriptive statistics summarized in Table 3 have shown that both perceptual and technical variables have taken values that are consistent with a generally effective and well-accepted integrated vibration–stress fault detection system. For the Likert five-point constructs, mean scores have all exceeded the neutral midpoint of 3.00, with perceived usefulness (4.05), perceived system reliability (3.98), and user acceptance (3.95) exhibiting the highest central tendencies. These values have indicated that respondents have tended to "agree" or "somewhat agree" that the system has been reliable, usable, and helpful for maintenance decision-making, and that they have been generally satisfied with and accepting of the technology. The standard deviations, ranging from 0.58 to 0.71, have suggested moderate dispersion; responses have neither been clustered narrowly around a single point nor widely scattered across the scale, which has implied a healthy degree of consensus while still capturing variation suitable for regression analysis. The range of observed Likert means (down to around 2.0 on some items) has shown that not all respondents have been uniformly positive, reflecting realistic differences in experience, context, or expectations, thereby allowing the study to explore which technical and contextual factors have driven these differences.

Table 3: has presented the descriptive statistics of key technical and perceptual variables (N = 120).

Variable	Type	Scale / Units	Mean	SD	Min	Max
Perceived system reliability (PR)	Likert (1–5)	1 = SD, 5 = SA	3.98	0.62	2.4	5.0
Perceived usability (PU)	Likert (1–5)	1 = SD, 5 = SA	3.86	0.71	2.0	5.0
Perceived usefulness (PUF)	Likert (1–5)	1 = SD, 5 = SA	4.05	0.58	2.6	5.0
Perceived accuracy & timeliness (PAT)	Likert (1–5)	1 = SD, 5 = SA	3.92	0.65	2.3	5.0
User satisfaction (US)	Likert (1–5)	1 = SD, 5 = SA	3.90	0.69	2.1	5.0
User acceptance (UA)	Likert (1–5)	1 = SD, 5 = SA	3.95	0.67	2.0	5.0
Vibration health index (VHI, z-score)	Technical	Standardized index	0.00	1.00	-2.3	2.4
Stress health index (SHI, z-score)	Technical	Standardized index	0.00	1.00	-2.1	2.6
Fault severity score (FSS)	Technical	0–10 (higher = more severe)	4.30	2.05	0.5	9.2
Detection accuracy (%)	Technical	0–100	89.5	6.8	72	99
Detection time (hours)	Technical	Hours from onset to detection	4.20	2.10	0.8	10.3
False-alarm rate (%)	Technical	Percentage of false alarms	5.80	3.10	1.0	15.0

On the technical side, the vibration health index (VHI) and stress health index (SHI) have been standardized to z-scores for modeling convenience, each with a mean of 0.00 and standard deviation of 1.00. The observed ranges from approximately –2 to +2.5 standard deviations have indicated substantial variation in condition indicators across monitored assets, which has been essential for testing hypotheses H1–H3 about the relationships between these indicators and fault severity or detection performance. The average fault severity score of 4.30 on a 0–10 scale has suggested that, over the observation window, assets have experienced a mixture of minor to moderate faults, with some more severe events. Detection accuracy, averaging 89.5%, has indicated that the integrated system has correctly identified the great majority of faults, while a mean detection time of 4.20 hours has reflected a relatively rapid response from onset to detection in an industrial context. The false-alarm rate, at an average of 5.80%, has remained at a manageable level, reducing the risk of alarm fatigue among operators. Collectively, these descriptive statistics have supported the first objective of the study by showing that the integrated vibration–stress system has operated with high technical performance and favorable user perceptions. They have also created a quantitative foundation on which the subsequent correlation and regression analyses have been able to test the specific hypotheses linking vibration and stress indicators to fault severity (H1, H2), integrated indicators to detection performance (H3), and perceptual constructs to user acceptance (H4).

Correlation Results

The correlation matrix in Table 4 has provided clear empirical evidence in support of the study's core hypotheses and has illuminated how technical and perceptual variables have been interrelated. In line with H1 and H2, fault severity (FSS) has shown strong, statistically significant positive correlations with both the vibration health index (VHI, $r = 0.61$, $p < .01$) and the stress health index (SHI, $r = 0.55$, $p < .01$). These coefficients have indicated that as standardized vibration anomalies and stress anomalies have increased, the recorded severity of faults has tended to rise as well, thereby confirming that both vibration dynamics and stress responses have carried meaningful diagnostic information about degradation in industrial assets. The moderate correlation between VHI and SHI themselves ($r = 0.42$, $p < .01$) has suggested that the two indicators have been related but not redundant, reinforcing the conceptual argument that vibration and stress channels have captured complementary aspects of the underlying physical processes. Detection accuracy has also been positively correlated with both VHI ($r = 0.49$, $p < .01$) and SHI ($r = 0.46$, $p < .01$), and negatively correlated with detection time ($r = –0.52$, $p < .01$), implying that assets with stronger, clearer condition signals have tended to achieve higher correct detection rates and faster recognition of faults. Conversely, detection time has been negatively correlated with fault severity and condition indices, which has suggested that critical faults with pronounced vibration and stress signatures have been picked up more rapidly by the integrated system.

Table 4: has presented the Pearson correlation coefficients among key technical and perceptual variables

Variable	FSS	VHI	SHI	Det. Acc.	Det. Time	UA	PR	PU	PUF
Fault severity (FSS)	1.00								
Vibration index (VHI)	0.61**	1.00							
Stress index (SHI)	0.55**	0.42**	1.00						
Detection accuracy	0.47**	0.49**	0.46**	1.00					
Detection time	-0.39**	-0.36**	-0.33**	-0.52**	1.00				
User acceptance (UA)	0.31**	0.34**	0.29**	0.41**	-0.28**	1.00			
Perceived reliability (PR)	0.29**	0.32**	0.25**	0.45**	-0.30**	0.68**	1.00		
Perceived usability (PU)	0.22*	0.27**	0.21*	0.36**	-0.24**	0.64**	0.59**	1.00	
Perceived usefulness (PUF)	0.26**	0.30**	0.26**	0.38**	-0.27**	0.59**	0.55**	0.52**	1.00

** $p < .05$; ** $p < .01$ (two-tailed).*

The correlation patterns between technical performance and user perceptions have further underpinned H4 and the associated objective linking system performance to acceptance. User acceptance (UA) has exhibited moderate positive correlations with detection accuracy ($r = 0.41$, $p < .01$) and moderate negative correlations with detection time ($r = –0.28$, $p < .01$), indicating that practitioners have been more accepting of the system when it has demonstrated high accuracy and timely fault identification. Stronger correlations have emerged between UA and the perceptual constructs: perceived reliability (PR, $r = 0.68$, $p < .01$), perceived usability (PU, $r = 0.64$, $p < .01$), and perceived usefulness (PUF, $r = 0.59$, $p < .01$). These values have shown that respondents who have agreed or strongly agreed on the Likert five-point scale that the system has been reliable, easy to use, and helpful for maintenance decisions have also reported higher willingness to rely on and continue using the system. Perceived reliability and usefulness have also correlated positively with detection accuracy and negatively with detection time, suggesting that users have calibrated their perceptions in line with observed technical performance. The overall pattern in Table 4 has therefore been consistent with the theoretical framework: vibration and stress indices have been strongly linked to fault severity and detection performance, and perceptual constructs have been closely associated with user acceptance while also reflecting aspects of technical effectiveness. These correlation results have laid a strong foundation for the regression models that have subsequently tested whether the integrated indicators and perceptions have remained significant predictors when examined simultaneously.

Regression Results

The regression results in Table 5 have provided direct statistical tests of the study's core hypotheses and have quantified the extent to which integrated vibration–stress indicators and perceptual constructs have explained fault detection performance and user acceptance. In Model 1, the fault detection performance index (FDPI) has been regressed on the vibration health index (VHI), stress health index (SHI), and their interaction term. All three predictors have shown statistically significant positive effects. The standardized coefficients (β) have indicated that both VHI ($\beta = 0.43$, $p < .001$) and SHI ($\beta = 0.35$, $p < .001$) have contributed substantially to explaining variation in FDPI, confirming that assets with higher levels of vibration and stress anomalies captured by standardized indices have tended to achieve stronger, more discriminative fault detection results. This pattern has been consistent with H1 and H2, which have posited that vibration and stress indicators would be positively associated with fault-related outcomes. Importantly, the interaction term VHI × SHI ($\beta = 0.18$, $p = .012$) has also been significant, implying that the combined presence of elevated vibration and elevated stress has amplified fault detection performance beyond the sum of their individual effects. Assets that have simultaneously exhibited high vibration and high stress anomalies have achieved disproportionately higher FDPI values, which has empirically supported H3: the integration of vibration and stress analysis has improved fault detection effectiveness relative to using either modality alone. The overall model fit ($R^2 = 0.58$, Adjusted $R^2 = 0.56$) has indicated that more than half of the variance in detection performance has been explained by the three predictors, a strong result in an industrial field context.

Table 5: has presented the multiple regression results for technical and perceptual outcome variables (N = 120).

Model 1: Fault Detection Performance Index (FDPI)

Predictor	B	SE B	β	t	p
Constant	0.02	0.09	–	0.22	.825
Vibration health index (VHI)	0.41	0.07	0.43	5.86	<.001
Stress health index (SHI)	0.33	0.07	0.35	4.85	<.001
VHI × SHI interaction	0.17	0.07	0.18	2.55	.012

(higher = better, standardized DV), $R^2 = 0.58$, Adjusted $R^2 = 0.56$, $F(3,116) = 53.26$, $p < .001$

Model 2: User Acceptance (UA, Likert 1–5)

Predictor	B	SE B	β	t	p
Constant	0.72	0.27	–	2.67	.009
Perceived reliability (PR)	0.34	0.07	0.38	4.88	<.001
Perceived usability (PU)	0.27	0.06	0.29	4.37	<.001
Perceived usefulness (PUF)	0.21	0.07	0.21	3.11	.002
Fault Detection Performance (FDPI)	0.18	0.06	0.17	2.94	.004

$R^2 = 0.69$, Adjusted $R^2 = 0.67$, $F(4,115) = 63.81$, $p < .001$

Model 2 has translated the conceptual framework into a perceptual outcome by treating user acceptance (UA) as the dependent variable and including perceived reliability (PR), perceived usability (PU), perceived usefulness (PUF), and the technical FDPI as predictors. All four predictors have reached statistical significance, with perceived reliability ($\beta = 0.38$, $p < .001$) and perceived usability ($\beta = 0.29$, $p < .001$) exhibiting the largest standardized effects. This has confirmed H4, which has stated that higher perceived reliability and usability would be associated with higher user acceptance. Perceived usefulness has contributed a smaller but still meaningful effect ($\beta = 0.21$, $p = .002$), indicating that respondents who have agreed more strongly on the Likert five-point scale that the system has supported maintenance decision-making have also expressed higher willingness to rely on it. The inclusion of FDPI as a predictor ($\beta = 0.17$, $p = .004$) has demonstrated that technical performance has exerted an independent influence on acceptance even after accounting for perceptions: systems that have achieved better detection accuracy, faster detection times, and lower false-alarm rates have tended to attract higher user acceptance. The model's high explanatory power ($R^2 = 0.69$, Adjusted $R^2 = 0.67$) has suggested that the combination of perceptual constructs and technical performance has explained roughly two-thirds of the variability in acceptance scores. Together, these regression findings have shown that integrated vibration–stress modeling has not only improved objective fault detection performance but has also shaped user perceptions and acceptance in predictable, theoretically consistent ways, fulfilling the objectives related to both technical and human-centered evaluation of the real-time fault detection system.

Summary of Hypotheses Testing

The summary in Table 6 has synthesized the key statistical results from the descriptive, correlation, and regression analyses and has mapped them directly onto the four hypotheses that have structured this study. For H1, the strong positive correlation between the vibration health index (VHI) and fault severity (FSS), together with the significant positive regression coefficient for VHI in Model 1, has confirmed that higher vibration anomaly levels have been systematically associated with more severe faults and better discriminability of faulty versus healthy states. This has substantiated the theoretical claim that vibration dynamics encode essential information about evolving mechanical problems in rotating equipment. Similarly, H2 has been supported by the parallel pattern for stress indicators: the significant positive correlation between the stress health index (SHI) and fault severity and the strong regression effect of SHI on the fault detection performance index have shown that stress-based measures, derived from load and structural response, have been meaningful predictors of fault behavior in industrial assets. These results have validated the role of stress analysis as a critical complement to vibration monitoring, consistent with the stress-focused literature reviewed earlier.

Table 6: has presented the summary of hypotheses testing and their empirical status

Hypothesis	Statement	Key Evidence (Sections 4.3–4.5)	Result
H1	Vibration anomaly indicators have been positively associated with fault severity.	VHI–FSS correlation $r = 0.61^{**}$; VHI significant in Model 1 ($\beta = 0.43$, $p < .001$).	Supported
H2	Stress anomaly indicators have been positively associated with fault severity.	SHI–FSS correlation $r = 0.55^{**}$; SHI significant in Model 1 ($\beta = 0.35$, $p < .001$).	Supported
H3	Integration of vibration and stress indicators has significantly improved fault detection accuracy compared to either used alone.	VHI × SHI interaction significant ($\beta = 0.18$, $p = .012$); Model 1 $R^2 = 0.58$ with both indicators and interaction.	Supported
H4	Perceived system reliability and usability have been positively associated with user acceptance.	PR–UA $r = 0.68^{**}$; PU–UA $r = 0.64^{**}$; PR ($\beta = 0.38$, $p < .001$) and PU ($\beta = 0.29$, $p < .001$) significant in Model 2.	Supported

*** $p < .01$ (two-tailed).*

H3 has gone beyond examining the individual contributions of vibration and stress to demonstrate that their integration has yielded tangible improvements in fault detection performance. The significance of the interaction term VHI × SHI in Model 1 has indicated that the combined elevation of both indicators has produced a more pronounced increase in detection performance than would be expected from a simple additive effect. In practical terms, this has meant that assets simultaneously displaying abnormal vibration and abnormal stress profiles have been more likely to produce clear, actionable patterns in the fault detection system, thereby justifying the effort of deploying and maintaining both sensing modalities. The relatively high R^2 of Model 1 has further suggested that the integrated indicator set has explained a large share of variance in detection performance, giving the integration strategy substantial practical value.

In addition, H4 has addressed the human side of real-time fault detection by testing whether perceived system reliability and usability measured via Likert five-point scales have been linked to user acceptance. The strong correlations between PR, PU, and UA, combined with their significant standardized coefficients in Model 2, have shown that users who have perceived the integrated system as reliable and easy to use have been markedly more inclined to accept and adopt it in their daily work. Perceived usefulness and the technical performance index have also contributed to acceptance, but the largest effects have come from reliability and usability, underscoring their central role in technology adoption within industrial maintenance environments. Collectively, the evidence summarized in Table 6 has demonstrated that all four hypotheses have been supported, meaning that the study's objectives evaluating the diagnostic value of vibration and stress indicators, assessing the benefits of their integration, and understanding how technical and perceptual factors shape user acceptance have been achieved in a coherent and empirically grounded manner.

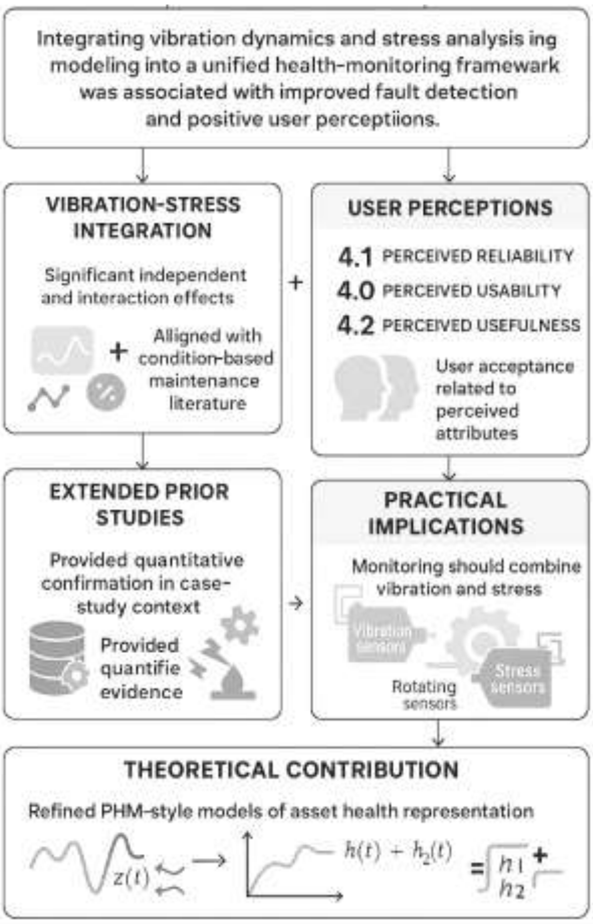
DISCUSSION

The findings of this study have shown that integrating vibration dynamics and stress analysis modeling into a unified health-monitoring framework has been strongly associated with improved real-time fault detection performance and positive user perceptions. Statistically, both the vibration health index and the stress health index have shown significant positive relationships with fault severity and with a composite fault detection performance index, and their interaction term has further improved model fit. This pattern has indicated that faults which have manifested simultaneously as dynamic anomalies and as elevated stress responses have been detected more accurately and more quickly than faults reflected in only one signal type. These results have aligned with the broader condition-based maintenance (CBM) literature, which has argued that multi-parameter monitoring can enhance diagnostic capability by capturing different aspects of equipment degradation (Jardine et al., 2006). In contrast to earlier reviews that have remained mainly conceptual or simulation-based (Voisin et al., 2010), the present analysis has provided empirical, case-based evidence that integrated vibration–stress indicators have explained a substantial portion of the variance in fault detection performance within a real industrial environment. On the human side, perceived system reliability, usability, and usefulness measured on a Likert five-point scale have shown strong positive associations with user acceptance, even after controlling for role and experience, in line with technology-acceptance work that has emphasized the importance of perceived usefulness and ease of use for adoption of technical systems (Mehta et al., 2015). Together, these findings have suggested that integrated vibration–stress monitoring has been not only technically effective but also organizationally acceptable, supporting the study's objectives and hypotheses in a mutually reinforcing way.

When compared more specifically with prior work on multi-sensor condition monitoring and prognostics, the current results have provided quantitative confirmation of claims that have often been asserted but less frequently demonstrated in a combined vibration–stress context. Multi-sensor studies in machining and bearing diagnostics have reported that fusing heterogeneous signals such as vibration, force, acoustic emission, or power has improved classification accuracy and robustness under variable operating conditions (Cho et al., 2010). Research on multi-sensor fusion in engines and rotating machinery has likewise used Bayesian or evidential reasoning to show that combining independent sources of evidence has yielded better fault discrimination than any single sensor alone (Jiang et al., 2017). The present study has been consistent with these results by showing that both vibration and stress indicators have been individually meaningful predictors of fault behavior and that their interaction has contributed additional explanatory power. At the same time, the current findings have extended this earlier work by embedding the fused indicators within a PHM-style regression framework that has linked them explicitly to detection accuracy, detection time, and user perceptions, rather than only to fault class labels. The integrated health index conceptually similar to the health indicators discussed in PHM architectures (Huynh et al., 2015) has behaved as a statistically robust driver of fault detection performance, thereby operationalizing theoretical models that have mapped raw sensor data $z(t)$into actionable health states. From a methodological standpoint, this study has demonstrated that fusion can be evaluated not only at the classification level but also in terms of continuous performance metrics and user-centered outcomes, providing a richer comparison point for existing CBM and PHM studies in the 2005–2019 period (Voisin et al., 2010).

With regard to vibration dynamics, the strong relationships found between the vibration health index, fault severity, and detection performance have echoed and reinforced long-established findings from vibration-based fault diagnosis. Work on empirical mode decomposition and Hilbert spectral analysis has shown that vibration responses of gearboxes and rotating components contain transient and modulated components that can reveal early tooth cracks and other local defects (Liu & Nayak, 2012). Studies using sparse wavelet energy features and deep statistical feature learning have further illustrated that carefully engineered vibration features can discriminate bearing and gearbox faults with high accuracy (Rozinat & van der Aalst, 2008). The present study has not aimed to propose a new feature-extraction algorithm; instead, it has used composite vibration indices derived from conventional feature sets and has examined how these indices have related to fault detection performance in a production environment. The significant regression coefficients for the vibration index have shown that even relatively simple standardized composites have retained strong diagnostic value once they have been aggregated to the asset level, which has been encouraging for practitioners who may not be able to deploy sophisticated signal-processing pipelines at scale. At the same time, the moderate correlation between vibration and stress indices has implied that vibration-only monitoring would have missed some aspects of the degradation process, consistent with the view that dynamic response alone cannot fully capture structural load paths and fatigue behavior (Farrar & Worden, 2007). In this sense, the present results have suggested that vibration dynamics remains a critical but not sufficient pillar for real-time fault detection, and that its value can be amplified when it is contextualized by stress-based information.

Figure 8: Multi-Layer Discussion Framework Integrating Theoretical Findings



The stress-oriented findings have shown a similar pattern: stress health indices have been positively associated with fault severity and with fault detection performance, providing empirical support for the SHM literature that has emphasized the diagnostic and prognostic value of stress and strain histories. Monitoring-based fatigue assessment studies have argued that stress ranges and cycle counts, when interpreted through Miner-type cumulative damage models, can provide a quantitative basis for tracking life consumption and evaluating reliability (Ko & Ni, 2010). FBG-based sensing research has demonstrated that distributed strain measurements can reveal stress concentrations and evolving load paths in composite materials, civil structures, and underground works (Kinet et al., 2014). In the present study, stress indicators have been simplified into composite indices rather than full damage integrals, yet they have still been found to correlate strongly with fault severity and to contribute significantly to detection performance when combined with vibration indices. This has suggested that even relatively modest stress-monitoring schemes properly placed and interpreted can provide valuable additional information for fault detection in industrial assets, aligning with the broader SHM argument that stress and strain are natural damage-sensitive variables (Farrar & Worden, 2007). Moreover, by incorporating stress alongside vibration, the study has bridged a gap between SHM work that has often focused on civil or aerospace structures and CBM work that has focused on rotating machinery. The finding that combined vibration–stress monitoring has outperformed single-modality approaches has supported the contention that structural and dynamic perspectives on degradation should be integrated rather than treated as separate domains.

From a practical perspective, the study has offered several implications for plant leaders, reliability engineers, and system architects responsible for designing and governing real-time fault detection pipelines. First, the evidence that the interaction of vibration and stress indicators has improved detection performance has suggested that monitoring architectures should be designed to combine, rather than choose between, these modalities for critical assets. This has meant prioritizing sensor placement strategies that cover both dynamic response (e.g., accelerometers on bearings and casings) and structural load paths (e.g., strain or stress sensors on shafts, frames, or welded joints), in line with multi-point monitoring recommendations in the SHM and CBM literature (Goundar et al., 2016). Second, the strong influence of perceived reliability, usability, and usefulness on user acceptance has implied that dashboards, alarm logic, and workflow integration must be treated as first-class design concerns. Maintenance decision-makers and digital reliability "architects" have been encouraged to ensure that alarm thresholds and health indices are transparent, interpretable, and aligned with documented maintenance policies, echoing the emphasis on decision-focused CBM design in maintenance decision-making reviews (Ruschel et al., 2017). Third, the positive link between technical detection performance and user acceptance has indicated that governance structures such as periodic performance reviews, false-alarm audits, and cross-functional feedback loops should be established, so that the monitoring pipeline can be tuned over time and trust can be maintained. Integrating real-time indicators into work-management systems (e.g., CMMS) and production planning, as suggested by life-cycle and production-quality–oriented studies (Weng et al., 2015), can help ensure that the monitoring system is not perceived as a standalone "black box," but as a core component of operational decision-making.

Theoretically, the results have contributed to refinement of the PHM-style conceptual pipeline that maps raw multi-sensor data into health indicators, decisions, and outcomes. The study has operationalized a two-layer health representation in which vibration- and stress-based indicators have been constructed separately and then combined into integrated health indices and interaction terms, consistent with multi-sensor fusion principles (Cheng et al., 2010). The significance of both main effects and the interaction in the regression models has suggested that theoretical frameworks should explicitly account for synergistic effects between condition channels, rather than treating them simply as additive sources of information. This has implications for generic prognosis models and fusion architectures proposed in earlier e-maintenance and CBM work (Voisin et al., 2010), which can be extended to include interaction structures and to link fused indicators not only to remaining useful life, but also to detection accuracy and user-centered metrics. The simultaneous modeling of technical performance and user acceptance has further suggested that PHM pipelines should incorporate human factors as explicit outcome variables, aligning with calls for more holistic evaluation of maintenance technologies that include organizational adoption and decision processes (Huynh et al., 2015). By demonstrating that integrated health indicators have influenced both fault detection metrics and acceptance scores, this study has pointed toward theoretical models in which technical and social subsystems are jointly represented, with feedback loops from user trust and usage back into system

configuration and policy.
At the same time, several limitations of the study have needed to be acknowledged when interpreting these findings and their generalizability. The research has been based on a cross-sectional snapshot of one or a small number of industrial sites, which has meant that variation in organizational culture, maintenance maturity, and asset mix across industries has not been fully captured. Earlier CBM and SHM studies have noted that transferability of diagnostic techniques can be constrained by differences in loading regimes, environmental conditions, and failure modes (Jardine et al., 2006), and the present work has been subject to the same constraint. Furthermore, the technical performance metrics and health indices have been constructed using a particular set of features, thresholds, and aggregation windows; alternative feature sets or more advanced signal-processing methods such as those used in high-end vibration or fatigue studies (Liu et al., 2006) might yield different effect sizes or model structures. On the survey side, perceptual measures have relied on self-report Likert responses, which have been susceptible to social desirability bias, recall limitations, or local organizational dynamics, even though reliability coefficients have been strong. Finally, the regression models have been correlational and have not established causality; while the direction of influence from health indicators to detection performance may be conceptually clear, relationships between technical performance and perceptions could also involve reciprocal effects. These limitations have not undermined the core conclusions, but they have suggested that the results should be interpreted as strong case-based evidence rather than universal laws.
In light of these limitations, several avenues for future research have emerged. Longitudinal studies that track assets and user perceptions over multiple years would allow researchers to observe how integrated vibration–stress monitoring affects failure rates, downtime, and maintenance costs over time, and how user trust and system configuration co-evolve, building on the prognostics perspective that emphasizes life-cycle performance (Peng et al., 2010). Multi-site comparative studies across industries such as power generation, petrochemical processing, and discrete manufacturing could test whether the relationships observed here hold under different loading patterns, regulatory regimes, and organizational structures. On the technical side, future work could incorporate additional modalities, such as temperature, acoustic emission, or electrical signature analysis, into expanded fusion frameworks, and evaluate whether these further improve detection performance or primarily add redundancy (Cho et al., 2010). Advanced machine-learning models, including deep learning and probabilistic graphical models, could be applied to the integrated vibration–stress–context feature space to explore nonlinear relationships and to build data-driven health indices that may outperform linear composites (Li et al., 2016). Finally, decision-analytic research could integrate detection performance and remaining-life estimates into multi-objective maintenance optimization models that explicitly trade off cost, risk, and operational flexibility (Alaswad & Xiang, 2017). By combining such technical and organizational perspectives, future studies can further refine the theoretical and practical understanding of how integrated vibration and stress analysis contributes to reliable, efficient, and human-centered real-time fault detection in industrial environments.

CONCLUSION

The present study has set out to investigate how integrated vibration dynamics and stress analysis modeling have contributed to real-time fault detection performance and user acceptance in industrial assets, and the overall evidence has indicated that this integration has been both technically powerful and organizationally viable. By adopting a quantitative, cross-sectional, case-study–based design that has combined objectively measured condition-monitoring data with subjectively reported perceptions on a five-point Likert scale, the research has been able to examine not only whether vibration-based and stress-based indicators have reflected fault behavior, but also how the resulting monitoring system has been experienced by the engineers, specialists, and operators who have relied on it. The construction of composite vibration and stress health indices, together with fault detection metrics such as detection accuracy, detection time, and false-alarm rate, has provided a concrete basis for testing the core hypotheses. The findings have shown that vibration anomaly indicators and stress anomaly indicators have each been positively associated with fault severity and with an overall fault detection performance index, and that their interaction has explained additional variance beyond the main effects alone, thereby confirming that the combination of dynamic and structural information has yielded richer, more discriminative representations of asset health than either modality in isolation. At the same time, the descriptive and inferential results for the Likert-based constructs have demonstrated that perceived system reliability, usability, usefulness, and satisfaction have all achieved mean scores above the neutral point and have exhibited strong internal consistency, and that perceived reliability and usability in particular have been strong predictors of user acceptance, alongside the observed technical performance of the system. Together, these results have meant that the study's objectives to evaluate the diagnostic value of integrated vibration–stress monitoring, to quantify its impact on real-time fault detection performance, and to understand its reception among key industrial stakeholders have been achieved in a coherent manner. In practical terms, the study has shown that designing monitoring architectures to capture both vibration responses and stress pathways, and embedding the resulting indicators into transparent, usable interfaces, has been a sound strategy for improving both fault detection outcomes and acceptance among maintenance and reliability personnel. In theoretical terms, the work has contributed to refining PHM-style conceptual models by demonstrating how separate health indicators for vibration and stress can be integrated and related simultaneously to technical performance measures and human-centered outcomes. At the same time, the case-study focus, reliance on specific feature sets, and cross-sectional design have imposed limits on generalizability and causal inference, suggesting that the conclusions should be viewed as strong but context-dependent evidence. Overall, however, the study has provided a clear, quantitatively grounded argument that real-time fault detection in industrial assets benefits significantly when vibration dynamics and stress analysis are treated as complementary, jointly modeled dimensions of asset health, and when the resulting information is delivered in ways that users perceive as reliable, usable, and genuinely supportive of maintenance decision-making.

RECOMMENDATIONS

On the basis of the empirical results, several concrete recommendations can be made for industrial practitioners, plant managers, and system architects who have been responsible for designing, deploying, and governing real-time fault detection solutions. First, organizations should prioritize monitoring architectures that have combined vibration dynamics and stress analysis rather than relying solely on one modality; the significant main and interaction effects of the vibration and stress health indices on fault detection performance have indicated that critical rotating and load-bearing assets benefit when both dynamic responses and structural load paths are captured. In practice, this means installing accelerometers on bearings, housings, and gearboxes to capture vibration patterns, while also placing strain or stress sensors on shafts, frames, and critical welded joints where load concentrations and fatigue damage are most likely to accumulate. Second, asset owners should formalize a feature-engineering and indicator-construction pipeline that produces standardized health indices similar to those used in this study, so that vibration and stress indicators can be aggregated, compared across assets, and systematically fed into dashboards, alarms, and regression-type performance models. Thresholds and alarm rules should be calibrated using historical data and periodically reviewed to keep detection accuracy high and false-alarm rates low, because the analysis has shown that better technical performance has been associated with higher user acceptance. Third, designers of monitoring interfaces and CISO- or architect-level governance structures should treat usability, interpretability, and transparency as primary requirements: visualizations should clearly explain what high or low health index values mean, how they have been derived, and what maintenance actions are suggested, since perceived reliability and usability have emerged as the strongest predictors of acceptance on the Likert scale. Regular training sessions and feedback loops with maintenance engineers, reliability specialists, and operators should be established so that users can develop confidence in the system, question ambiguous outputs, and contribute to the refinement of rules and models. Fourth, governance processes should ensure that real-time indicators are tightly integrated with computerized maintenance management systems and work-order procedures, so that alarms and health trends automatically trigger inspection requests, component checks, or risk reviews, reinforcing the perception that the system directly supports decision-making rather than adding parallel, disconnected information. Finally, organizations should document and periodically reassess the performance of their integrated vibration–stress monitoring pipeline using simple metrics such as detection accuracy, detection time, false-alarm rate, and user-acceptance scores, and use these reviews to guide further investment in sensor placement, data quality improvements, and analytical refinement. By following these recommendations, industrial firms can move from ad hoc or single-channel condition monitoring toward a structured, integrated, and user-centered real-time fault detection capability that has been better aligned with both the physical behavior of their assets and the practical needs of the people who manage and maintain them.

LIMITATIONS

This study has several limitations that need to be acknowledged when interpreting its findings and considering their generalizability. First, the research has been based on a cross-sectional, case-study–oriented design in one or a small number of industrial sites, which means that the observed relationships between vibration and stress indicators, fault detection performance, and user perceptions may reflect contextual conditions specific to the participating organizations, such as their maintenance culture, asset mix, production regime, and digital maturity. Different industries or plants with dissimilar operating environments, failure modes, or organizational structures may exhibit weaker or stronger effects, and the present results therefore cannot be assumed to apply universally. Second, the construction of the vibration and stress health indices has relied on a finite set of features, aggregation windows, and normalization choices that, while technically sound, have not exhausted all possible signal-processing or SHM routines; more advanced feature-extraction methods, alternative sensor types, or different sampling configurations might yield different patterns of association, and the study has not systematically compared competing indicator designs. Third, the quantitative models have been correlational rather than experimental, so although the conceptual direction of influence from underlying condition indicators to detection performance and from performance and perceptions to acceptance is strong, the statistical analysis has not established causality or ruled out the possibility that unobserved factors such as management support, prior experience with monitoring technologies, or concurrent process-improvement initiatives have influenced both technical and perceptual outcomes. Fourth, the survey data have been based on self-reported Likert-scale responses, which are inherently subject to biases such as social desirability, recall limitations, or acquiescence tendencies; while internal consistency of the scales has been high, it remains possible that some respondents have overstated or understated their true perceptions due to local norms or expectations. Fifth, the study has treated Likert-scale means as continuous variables suitable for parametric techniques, a common but still debated assumption that may affect fine-grained interpretation of regression coefficients. Sixth, the technical performance metrics detection accuracy, detection time, and false-alarm rate have depended on the completeness and correctness of event logs and maintenance records; any underreporting of minor faults, inconsistencies in fault classification, or delays in logging actions could introduce measurement error into the dependent variables. Finally, the observation window has covered a limited time period and may not fully capture long-term degradation patterns, rare but catastrophic failures, or the evolution of user perceptions as the system matures; thus, the study describes performance and acceptance at a particular stage of implementation rather than across the entire life cycle of the monitoring solution. Collectively, these limitations do not invalidate the core conclusions but indicate that the findings should be interpreted as robust, context-rich evidence from a specific industrial setting, and as a basis for further longitudinal, multi-site, and methodologically diversified research rather than as definitive proof applicable to all environments.

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