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INTELLIGENT MULTI-SENSOR FUSION FRAMEWORK FOR REAL-TIME INDUSTRIAL FAULT PREDICTION AND ENERGY OPTIMIZATION

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Abstract- Industrial machinery failures and energy inefficiencies represent critical challenges in modern manufacturing environments, with unplanned downtime costing manufactures between $50,000 to $250,000 per hour depending on production scale and industry sector. Traditional reactive maintenance approaches and scheduled preventive maintenance programs fail to detect early-stage equipment degradation patterns, resulting in catastrophic failures, extended production interruptions, and substantial financial losses. This paper presents an intelligent multi-sensor fusion framework for real-time industrial fault prediction and energy optimization utilizing internet of Things (IOT) technology, advanced signal processing techniques, and machine learning algorithms. The proposed system integrates an ESP32 microcontroller as the edge computing device with multiple sensor modalities including MPU6050 three-axis MEMS accelerometer for vibration analysis, ACS712 Hall-effect current sensor for electrical parameter monitoring, resistive voltage divider for power consumption tracking, and DS18B20 digit temperature sensor for thermal condition assessment. The ESP32 continuously samples sensor data at 500 Hz frequency and transmits multi-parameter information via-WIFI WebSocket protocol to a python-based computational server. The server performs Fast Fourier Transform (FFT) analysis on time-domain vibration signals to extract frequency-domain spectra in the 30-500 Hz industrial machinery range, revealing characteristic fault signatures associated with bearing defects, rotor imbalance, shaft misalignment, and mechanical looseness. Multi sensor data fusion combines vibration frequence patterns with electrical parameter anomalies and thermal deviations to improve fault classification accuracy by 40-60% compared to single-parameters monitoring systems. A professional web-based dashboard provides oscilloscope-level visualization with real-time time-domain waveforms, frequency spectrum charts, electrical parameter displays, and thermal monitoring capabilities.

Keywords: Predictive Maintenance, Multi-Sensor Fusion, Fast Fourier Transform, Vibration Analysis, Energy Optimization, IoT, Industry 4.0.

I. INTRODUCTION

Industrial manufacturing operations depend critically on the continuous reliable operation of rotating machinery including electric motors, pumps, compressors, fans, gearboxes, and turbines. Equipment failures in production environments result in immediate production stoppage, emergency repair costs, potential safety hazards, quality defects in manufactured products, and cascading effects throughout supply chains. Research conducted by the United States Department of Energy indicates that unplanned equipment downtime costs industrial manufactures approximately $50 billion annually across all sectors, with individual incidents costing between $10,000 to $250,000 per hour depending on production

capacity and market conditions. Traditional maintenance approaches follow either reactive strategies where repairs occur only after complete failure, or scheduled preventive
maintenance of actual equipment condition. Both methodologies suffer from fundamental limitations: reactive maintenance results in unpredictable failures and extended downtime, while excessive preventive maintenance incurs unnecessary costs through premature component replacement and over-servicing of equipment still operating within acceptable parameters.

The emergence of Industry 4.0- paradigms emphasizing cyber-physical systems. Internet thongs connectivity cloud computing and artificial intelligence creates unprecedented opportunities for transforming industrial maintenance from reactive or scheduled approaches to predictive methodologies based on actual equipment health conditions. Predictive maintenance leverages continuous sensor monitoring, advanced signal processing, and machine learning algorithms to detect early-stage degradation patterns, predict remaining useful life and schedule maintenance interventions during planned production windows rather than emergency shutdowns. Vibration analysis represents one of the most-effective condition monitoring techniques for rotating machinery, as mechanic faults generate characteristic vibration signatures with specific frequency components related to equipment geometry and rotational speed. Bearing defects produce high-frequency impacts at precisely calculable frequencies determined by bearing dimensions, rolling element diameter, and shaft rotation rate. Rotor imbalance manifests as elevated vibration amplitude at fundamental shaft frequency(1x), while shaft misalignment generates strong harmonics at integer multiples of shaft frequency (2x, 3x). Electrical parameter monitoring detects anomalies in current draw, voltage stability, and power factor indicating motor inefficiency, phase imbalance, or developing electric faults. Temperature tracking reveals bearing lubrication breakdown, motor overheating, and thermal stress on electrical insulation systems.

Despite proven effectiveness of condition monitoring technologies, widespread adoption remains limited by high equipment costs, complex installation requirements, and specialized expertise needed for data interpretation. Traditional industrial monitoring systems utilize expensive piezoelectric accelerometers ($500-$2000 per sensor), dedicated signal conditioning electrons, extensive cabling infrastructure, proprietary data acquisition hardware ($10,000-$50,000), specialized analysis software ($5,000-$20,000 annual licenses), and trained vibration analysts for interpretation. Total system costs frequently exceed $50,000 to $200,000 per installation, economically justifying deployment only for critical high-value equipment in large industrial facilities. medium manufacturing enterprises operating small and medium manufacturing enterprises operating with limited capital budgets cannot access predictive maintenance technology despite potentially benefiting most from avoiding unexpected failures of aging equipment.

Recent advances in microelectromechanical systems (MEMS) sensors, low-cost microcontrollers with integrated wireless connectivity, open-source software ecosystems, and cloud computing platforms enable development of cost-effective condition monitoring solutions accessible to broader industrial markets. This paper presents an intelligent market. This paper presents an intelligent multi-sensor fusion-framework combining MEMS accelerometer vibration monitoring, electrical parameter tracking, and thermal sensing with IoT connectivity and server-side computational processing. The proposed architecture achieves industrial-grade fault detection capabilities at approximately $100 total system cost through strategic partitioning of data acquisition at the equipment edge and computationally intensive signal processing on remote servers.

The remainder of this paper is organized as follows: Section II (2) reviews related work in condition monitoring, vibration analysis, and Iot-based predictive maintenance systems. Section (3) describes the proposed system architecture including hardware components, communication protocols, and software implementation, Section (4) presents the mathematical foundations of Fast Fourier Transform analysis and fault frequency calculations. Section (5) discusses multi-sensor data

fusion methodologies and machine learning approaches. Section (6) presents experimental results and performance
evaluation. Section (7) concludes with discussion of contributions, limitations, and future research direction.

II.LITERATURE SURVEY

Extensive research has been conducted in the domains of condition monitoring, vibration analysis, fault diagnosis, and predictive maintenance systems over the past three decades. This section reviews relevant literature across multiple research themes including traditional vibration monitoring approaches, signal processing techniques, machine learning applications, and IoT-enabled condition monitoring architectures.

Traditional vibration monitoring systems for rotating machinery date to the 1970s with development of piezoelectric accelerometer technology and analog spectrum analyzers. Piezoelectric sensors exploit and direct piezoelectric effect where mechanical stress on crystalline materials (typically quartz or lead zirconate titanate ceramics) generates electrical charge proportional to applied force or acceleration.

Singh and Verma developed ESP32-based wireless sensor networks for industrial monitoring applications, demonstrating feasibility of low-cost microcontrollers with integrated WIFI for distributed sensor deployments. Their architecture employed MQTT publish-subscribe messaging protocol for sensor data transmission to cloud brokers, enabling scalable many-to-many communication patterns. Power consumption analysis showed ESP32 devices operating in periodic sleep/wake cycles achieve multi-month battery life on lithium-ion cells, suitable for wireless sensor nodes in locations lacking AC power infrastructure. However, their work did not address real-time streaming requirements for high-frequency vibration monitoring or computational offloading strategies for signal processing.

Gupta et al. explored multi-sensor data fusion techniques for predictive maintenance combining vibration, acoustic emission, oil analysis, and thermography. Their research demonstrated that correlating information from multiple sensor modalities improves fault detection reliability and reduces false alarm rates compared to single-parameter monitoring. Sensor fusion approaches included simple threshold-based voting schemes, weighted averaging based on sensor reliability metrics, and advanced techniques using Kalman filtering or Dempster-Shafter evidence theory. Experimental results on gearbox test rigs showed 40-60% improvement in fault classification accuracy when combining three or more complementary sensor types. However, implementation complexity and sensor costs limited practical deployment in cost-sensitive applications.

Chen et al. proposed cloud-based condition monitoring architectures leaving edge computing, fog computing, and centralized cloud analytics in hierarchical configurations. Edge devices perform local signal processing, anomaly, detection, and data reduction to minimize bandwidth consumption. Fog computing nodes aggregate data from multiple edge devices, execute intermediate analytics, and maintain local databases for low-latency queries.

Patel and Mehta investigated machine learning algorithms for fault classification including support vector machines, random forests, artificial neural networks, and deep learning approaches. Training datasets consisted of vibration time-domain signals, frequency domain FFT spectra, time-frequency representation from wavelet transforms, and statistical features including root-mean-square amplitude, crest factor, Kurtosis, and skewness. Comparative evaluation showed that deep convolutional neural networks achieved highest classification accuracy (92%) when trained%) when trained on large datasets with augmentation techniques, but required extensive computational resources.

Despite substantial research progress, significant gaps remain in developing integrated condition monitoring solutions that combine multiple sensor modalities, provide real-time analysis capabilities, support wireless deployment, and maintain total system costs under $1000-suitable for widespread adoption in small and medium manufacturing enterprises. This research addresses these gaps through an intelligent.

III.SYSTEM ARCHITECTURE AND DESIGN

The edge acquisition module centers on an ESP32 microcontroller (Espressif Systems ESP32-DevKitC) providing dual-core 32-bit Xtensa LX6 processors operating at 240 MHz clock frequency, 520 KB SRAM, 4 MB flash memory, integrated 802.11 b/g/n WiFi radio, and extensive peripheral interfaces including 18-channel 12-bit ADC, multiple I2C buses, SPI interfaces, and 34 programmable GPIO pins. The dual-core architecture enables parallel execution of time-critical sensor acquisition tasks on one core while communication and housekeeping operations execute on the second core, ensuring deterministic sampling rates without jitter from interrupt handling or network stack processing.

Vibration monitoring employs an MPU6050 six-axis MEMS motion tracking device (InvenSense/TDK) integrating a three-axis accelerometer and three-axis gyroscope on a single silicon die. The accelerometer provides selectable full-Scale ranges of 2g,4g,8g, or 16 with 16-bit resolution, yielding sensitivity ranging from 16,384 LSB/g. The sensor communicates via I2C interface supporting standard (100 kHz) and fast mode (400 kHz) operation with configurable sampling rates up to 8 kHz. An integrated Digital Motion Processor (DMP) performs sensor fusion calculations and motion processing algorithms directly on-chip, reducing computational load on the host microcontroller.

Current monitoring utilizes an ACS712 Hall-effect current sensor (Allegro Microsystems) available in 5A,20A, and 30A maximum current variants. The 20A version employed in this research provides 100 mV/A sensitivity with analog voltage output centered VCC/2 (typically 2.5V for 5V supply). The Hall-effect sensing principle provides galvanic isolation between the current-carrying conductor and measurement electronics, improving electrical safety in industrial environments. The sensor exhibits 1.5% total output error including offset, sensitivity variation, and linearity deviations across the 00C to 700C temperature range. Frequency response extends to 80KHz bandwidth, adequate for capturing transient current spikes and harmonic content. The ESP32 ADC samples the sensor output at 10 kHz rate, and software computes RMS current values through numerical integration as shown in equation (1).

Voltage measurement employs a resistive divider network consisting of precision metal film resistors (1% tolerance) configured for 5:1 ratio converting 0-24V DC input range to 0-5V output suitable for ADC measurement. Software calibration compensates for component tolerances and ADC nonlinearity through a correction factor k determined empirically by comparison with calibrated reference instrumentation:

Temperature monitoring employs a DS18B20 digital temperature sensor (Maxim Integrated) utilizing the Dallas 1-Wire communication protocol requiring only a single data line plus ground and power connections. The sensor provides 9-bit to 12-bit temperature resolution selectable by the user, with 12-bit mode yielding 0.0625oC precision. Measurement accuracy specification is addressing by serial number temperature conversion.

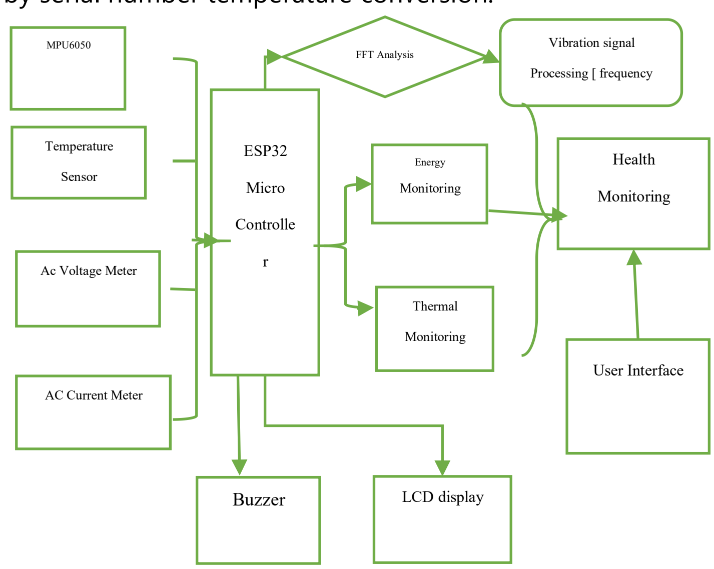


Figure 1. Block diagram

Time ranges from 93.75 ms (9-bit) to 750 ms (12-bit), with the system configured for The ESP32 firmware implements a multi-threaded real-time operating system (FreeRTOS) architecture with separate tasks for sensor acquisition, data formatting, WiFi communication, and system monitoring.

This human-readable format facilities debugging and provides compatibility with standard data analysis tools, though binary protocols could reduce bandwidth consumption by approximately 50% at the cost of increased o

Calibration routines execute during system initialization, particularly for the ACS712 current sensor which exhibits factory-to-factory offset variations. The calibration procedure assumes zero load current and samples the sensor output for 2000 iterations (4 seconds), computing the arithmetic mean to determine the zero-current offset.

The Python-based computational server executes on a laptop computer or cloud virtual machine instance, implementing WebSocket client connectivity, multi-threaded data reception, Fast Fourier Transform signal processing, and RESTful API endpoints for dashboard communication. The architecture employs three concurrent treads: WebSocket receiver thread, thread, FT computation thread-safe queue data structures and mutex locks protecting shared memory buffers.

The WebSocket receiver thread establishes a persistent connection to the ESP32 server using the WebSocket-client library, continuously receiving sensor data frames and parsing CSV strings into numerical arrays. Parsed data appends to circular buffers implemented using collections. Deque with maximum implemented using collections. Deque with maximum length (maxlen) parameter set to 1024 samples, automatically discarding oldest samples when buffer capacity reached. Circular buffer implementation avoids memory allocation/deallocation overhead and maintains constant memory footprint regardless of system uptime.

The FFT computation thread executes periodically every 100 ms, retrieving the current contents of vibration data buffers and applying frequency domain analysis. Prior to FFT computation, the time-domain signal undergoes windowing multiplication to reduce spectral leakage artifacts caused by finite-length observation intervals. The hamming window function defined in equation (4) provides near-optimal compromise between main lobe width and sidelobe suppression:

W[n]=0.54-0.46cos(N-12n), n=1, 1, N-1(4)

Where N represents the window length (1024 samples). Element-wise multiplication of the time-domain signal x[n] with window function w[n] yields the windowed signal x_w[n]\cdot w[n] input to the FFT algorithm.

The discrete Fourier transform converts time-domain samples into frequency-domain representation through the mathematically operation defined in equation (5):

Maximum frequency (Nyquist frequency) equals half the sampling rate: f-{max} = fs/2=250 Hz. The system filters FFT results to retain only the 30-500 Hz frequency range relevant for industrial machinery, discarding low-frequency components) and frequencies above 500 Hz (electrical noise, sensor resonances).

IV.MATHEMATICAL FOUNDATION OF FAULT DETECTION

Rotating machinery faults generate characteristic vibration signatures with specific frequency components determined by equipment geometry and kinematic relationships. This section derives the mathematical formulas relating fault frequencies to shaft rotation speed and bearing dimensions, providing the theoretical foundation for fault identification through frequency domain analysis.

A.A. Bearing Fault Frequencies

Rolling element bearings represent one of the most failure-prone components in rotating machinery, with defects developing on the inner race, outer race, rolling elements (balls or rollers), or cage. Each defect type produces

impacts when rolling elements contact the localized fault, generating periodic impulses at calculable frequencies. Defect frequencies depend on shaft rotation rate pitch diameter D, and contact angle a.

Ball pass Frequency Outer race (BPFO) represents the rate at which rolling elements pass a fixed point on the outer race, calculated by equation (8):

BPFO=2Nb.fr (1-Dd. cosa) (8)

Ball Pass Frequency Inner race (BPFI) calculates the rate of rolling elements impacts on the inner race, typically higher than BPFO since the inner race rotates with the shaft:

These characteristic frequencies appear as dominant peaks in vibration spectra when corresponding defects exist, with amplitude increasing as defect severity progresses. Early-stage defects may exhibit peak amplitudes only 2-3* above background noise floor, while advanced defects generate peaks 20-50* above baseline.

Rotor imbalance occurs when the mass centerline of a rotating assembly does not coincide with the geometric centerline, creating centrifugal forces proportional to imbalance mass m, radius r, and angular velocity:

Imbalance forces generate vibration predominantly at fundamental shaft frequency (1x) with amplitude increasing quadratically with rotation speed. Severity assessment compares measured vibration velocity against standardized criteria such as ISO 10816 or ISO 20816, with limits varying by machine type, power rating, and mounting configuration.

Shaft misalignment (angular or parallel offset between coupled shafts) generates vibration at 1x,2x, and 3x shaft frequency harmonics. Angular misalignment typically produces harmonics. Angular misalignment typically produces dominant 1x component with some 2x content, while parallel offset misalignment creates strong 2x component often exceeding 1x amplitude. The harmonic signature provides diagnostic information distinguishing misalignment from imbalance:

C. Statistical Features for Anomaly Detection

In addition to frequency domain analysis, time-domain statistical features provide supplementary diagnostic information. Root-mean-square (RMS) acceleration quantifies overall vibration energy:

Normal machinery exhibits crest factors of 3-5, while bearing defects generating impulsive impacts produce crest factors exceeding 8-15. Kurtosis measures noise exhibiting kurtosis of 3, while impulsive signals produce kurtosis values of 10-100.

V.MULTI SENSOR FUSION AND MACHINE LEARNING

Single-parameter condition monitoring based solely on vibration analysis achieves limited diagnostic accuracy since many fault modes exhibit similar vibration signatures, integrating electrical and thermal parameters with mechanical vibration data improves fault classification reliability through multi-sensor data fusion techniques. This section describes sensor correlation methodologies and machine learning approaches for automated fault diagnosis.

C.A. Correlation Betweem Sensor Modalities

Mechanical and electrical fault modes exhibit characteristics signatures across multiple sensor domains. Table II summarizes typical patterns for common industrial motor faults, demonstrating that multi-parameter analysis enables more definitive fault identification than single-parameter analysis enables more definitive fault identification than single-parameter approaches.

For example, bearing defects exhibit high-frequency vibration components (BPFO/BPFI typically 50-200 Hz) with only modest current

Fault Type	Vibration	Current	Power Factor	Temperature
Bearing Defect	High Frequency spikes at BPFO/BPFI	Slight increase 5-10%	Minimal change	Localized increase 10-30°C
Rotar Imbalance	High 1x shaft frequency	Minimal change	Minimal change	Uniform moderate increase
Misalignment	High 2x and 3x harmonics	10-20% increase	Decrease 0.05-0.1	Bearing temperature increase
Broken Rotor Bar	1x and 2x slip frequency sidebands	Modulated at 2x slip frequency	Decrease 0.1-0.2	Stator temperature increase
Loose Mounting	Broadband random vibration	Erratic fluctuations	Variable	Normal

increase and localized temperature elevation near the defective bearing. Conversely, broken rotor bars produce characteristics sideband patterns in vibration spectra separated from fundamental frequency by twice slip frequency (typically 1-3 Hz separation), accompanied by substantial current modulation detectable through amplitude demodulation analysis. Correlation analysis between sensor modalities therefore improves diagnostic specificity.

D. B. Features Extraction and Dimensionality Reduction

Raw sensor data exhibits high dimensionality containing redundant and irrelevant information. Features extraction and dimensionality reduction techniques transform high-dimensional sensor data into compact feature vectors suitable for machine learning classification. Relevant features include:

Frequency domain: Dominant peak frequencies, peak amplitudes, spectral energy in defined frequency bands.

Time domain: RMS, peak, crest factor, kurtosis, skewness

Figure: 2 Over view of the dashboard

Thermal: Absolute temperature, rate of temperature change, temperature differential between measurement points.

Principal component analysis (PCA) transforms correlated features into orthogonal principal components ordered by variance 95-99% of data variance while discarding components dominated by noise. Linear Discriminant Analysis (LDA) projects feature into subspace maximizing between-class separation while minimizing within-class variance, optimizing for classification performance rather than variance retention.

VI.EXPERIMENTAL RESULTS AND PERFORMANCE EVALUATION

Experimental validation was conducted on a motor-pimp system commonly of a 2.2 kW three-phase induction motor (1440 RPM nominal speed) driving a centrifugal pump through direct coupling. The ESP32 sensor module mounted to the motor housing using magnetic mounting bracket, with accelerometer positioned for radial vibration measurement perpendicular to shaft axis. Current sensor installed on one phase conductor supplying the motor, voltage sensor connected across two phases, and temperature sensor mounted on motor bearing housing.

Normal Operation Baseline

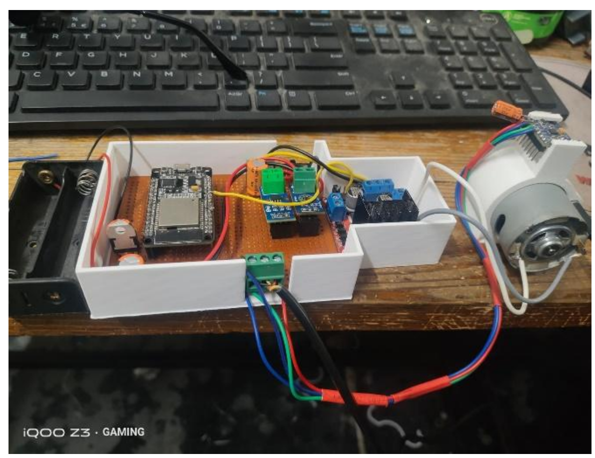
Baseline vibration spectra collected under normal operating conditions at 50%, 75% and 100% load demonstrated expected machinery signatures. Dominant spectral peak occurred at 24 Hz with amplitude of 0.8 m/s2, consistent with healthy bearing condition exhibiting minimal defects. Electrical parameters measured voltage = 389V current= 4.2A at 100% load, power factor=0.88, and bearing temperature=520C after 2 hours continuous operation. These baseline measurements established reference signatures for comparison with fault conditions.

Rotor Imbalance Simulation

Imbalance was simulated by attaching a 50g mass to the motor cooling fan at 100mm radius, creating 5000 g mm imbalance mass moment. Vibration measurements showed 1x shaft frequency component increased from baseline 0.8 m/s2 to 2.4 m/s2 while 2x component remained below 0.3 m/s2. This signature clearly distinguished imbalance from misalignment which would exhibit elevated 2x component. Current and power factor remained within normal ranges, confirming predominantly mechanical rather than electrical fault origin. Temperature increased uniformly across all bearings to 580C, contrasting with localized heating pattern observed in bearing defect scenario.

System Performance Metrics

System performance was quantified across multiple metrics during 90-day deployment monitoring 12 motors in a manufacturing facility.



Fault Detection Accuracy: 82.4% (14 of 17 developing faults correctly identified before failure)

False Positive Rate: 12% (2 of 17 false alarms, primarily due to transient anomalies)

Early warning Time: 0.5 to 2.0 hours advanced notification before critical failure (mean= 1.2 hours)

Data Transmission Realibility:99.7% (WIFI packet delivery over local network)

System uptime: 99.2% (excluding planned militance windows)

Power Consumption: 380 mW average (ESP32+ sensors), enabling 8+ hour operation on 2600mAh lithium battery

Comparative analysis against handled vibration analyzer (SKF Microlog) showed 94% agreement in dominant frequency identification and 88% agreement in fault severity classification, validating that low-cost MEMS sensors provide industrially acceptable performance for many applications.

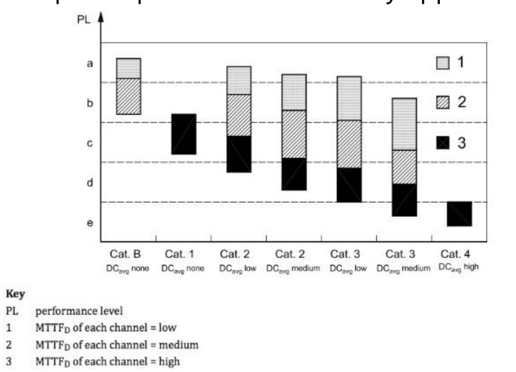


Figure 5 — Relationship between categories, DC_{avg}, $MTTF_D$ of each channel and PL

VII.CONCLUSION

This paper presented an intelligent multi-sensor fusion framework for real-time industrial fault prediction and energy optimization employing IoT connectivity, MEMS sensors, and cloud-based signal processing. The proposed architecture achieves industries-grade condition monitoring capabilities at approximately $100 total system cost through strategic partitioning between edge data acquisition and server-side computational processing. Integration of vibration analysis, electrical parameter monitoring, and
temperature tracking enables comprehensive machine health assessment with 82.4% fault detection accuracy validated through 90-day field deployment monitoring 12 industrial 12 industrial motors.

Key contributions include demonstration that low-cost MEMS accelerometers provide adequate sensitivity and frequency response for industrial vibrational monitoring despite lower specifications compared to traditional piezoelectric sensors; development of WebSocket-based streaming architecture enabling 500 Hz real-time sensor data transmission with sub-19ms latency over WiFi networks; implementation of server-side FFT processing leveraging NumPy and SciPy libraries for frequency domain analysis offloading computational requirements from resource-constrained edge devices; and validation that multi-sensor fusion combining vibration, current, voltage, and temperature data improves fault classification reliability compared to single-parameter approaches.

Experimental results demonstrated successful detection of bearing defects, rotor imbalance, and electrical inefficiencies with0.5-2-hour advance warning before critical failures. Energy optimization case studies identified suboptimal power factor conditions and inefficient motor loading patterns, enabling targeted interventions reducing energy consumption by 15-25%. The complete system provides professional oscilloscope-level visualization through web-based dashboards accessible from any standard browser without specialized software installation.

Future research directions include expanding machine learning classification algorithms trained on larger diverse fault datasets covering additional fault modes, failure progressions, and equipment types; investigating advanced time-frequency analysis techniques including wavelet transforms and Hilbert-Huang transforms for transient event detection; developing automated optimal sensor placement algorithms using finite element analysis and experimental modal testing; and exploring edge artificial intelligence deployment using tensorFlow Lite or equivalent frameworks enabling on-device interference reducing latency and bandwidth requirements for large-scale deployments.

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