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# Sensor Data Acquisition Techniques for Fault Detection in Mechanical Systems: A Review of Accuracy and Timeliness

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***Abstract*—The reliability of mechanical systems in industrial environments relies heavily on accurate and timely fault detection, which is made possible through efficient sensor data acquisition techniques. This review investigates the role of various sensors and acquisition methods in detecting faults in mechanical components, highlighting recent advances and applications. The study categorizes key sensor types such as temperature, motion, proximity, and chemical sensors and explores their roles in real-time monitoring and diagnostics. Further emphasis is placed on modern data acquisition techniques, including synchronization methods, signal preprocessing, and intelligent systems that enhance decision-making accuracy. It also explores the integration of machine learning (ML) and deep learning (DL) models in fault detection frameworks, which improve diagnostic efficiency and reduce dependency on manual inspection. Additionally, the review presents comparative findings from recent open-access studies to evaluate strengths, challenges, and future directions. The importance of accuracy and timeliness is discussed, emphasizing how delayed or incorrect detection can affect industrial productivity and safety. Overall, this review serves as a foundation for researchers and engineers seeking to develop or improve sensor-based fault detection systems in mechanical applications.**

***Keywords—Sensor data, acquisition, fault detection, mechanical systems, real-time monitoring, machine learning, industrial diagnostics, timeliness***

## I. INTRODUCTION

One essential component of industrial operations is thought to be mechanical machinery. They therefore have a significant impact on the manufacturing and production processes. Because of their significant role in the manufacturing line, they are frequently positioned in harsh settings and places, which leaves them vulnerable to a variety of defects and malfunctions. In complex sensor systems, faults are characterized by unforeseen events that might happen at a certain moment and cause larger occurrences or a chain of additional unforeseen events [1][2][3]. Sensors are widely used for acquiring information and signals, especially in environmental monitoring, aquaculture system monitoring, disease detection, machinery monitoring systems and agricultural monitoring [4]. Multi-sensor information fusion technology is becoming more and more necessary for intelligent systems as science and technology progress; it is becoming more and more significant in the field of industrial machinery and equipment malfunction detection. A single sensor is utilized in the majority of intricate industrial settings to obtain a particular piece of functional data from the mechanical machinery [5][6].

The specifics of data collection may change based on the types of behaviors being examined in the study. For instance, basic actions (i.e., coarse granularity) such as sitting and walking may be recognized by a waist sensor with a low sample rate. However, a single sensor worn around the waist might not provide adequate performance to detect combinatorial actions with finer granularity, such as eating and driving [7]. In order to provide the elderly a feeling of safety and trust, it is crucial that the activities of Daily Living (ADL) be classified promptly and accurately. Failure to do so might have serious repercussions, particularly in the event of an emergency occurrence like a fall [8].

The signal is obtained by asset monitoring sensors. Data that is Sensor measurements and algorithm processing must be accurate and timely in order for informed decisions based on data evidence to be made. Inaccurate categorization and interpretation, however, can have an impact on algorithms, particularly if sensors, which are also susceptible to malfunctions, provide inaccurate data. The maintenance plan that is chosen is then directly impacted by accuracy, and indirectly [9]. The goal of this review is to describe different techniques for obtaining data to help with fault detection in machines, mainly focusing on issues of accuracy and time. The main purpose of analyzing existing approaches, problems and development is to guide both theory and practice in industrial maintenance and reliability engineering.

### A. *Structure of the Paper*

The structure of this paper is as follows: Section II discusses sensor data acquisition techniques and types of sensors. Section III covers fault detection methods in mechanical systems. Section IV addresses accuracy and timeliness in fault diagnosis. Section V presents a literature review of recent advances. Section VI concludes with future research directions.

## II. CORE OF FAULT DETECTION IN MECHANICAL SYSTEMS

In dependable mechanical systems, fault diagnosis and detection are critical issues [10][11]. It is well known that relying on the state estimate residuals of observers is one of the most popular techniques for identifying and diagnosing faults. By determining whether or not the residual is zero, faults can be found. In this instance, the generated estimated residual may produce an incorrect detection result if the built observer is unable to appropriately estimate the states [12]. Gearboxes, ball-screws, hydraulic valves, and other components are frequently employed as actuators in mechanical gearbox systems. For example, in a conventional mechanical gearbox system, a gearbox typically drives the load. A servomotor then drives the gearbox.

### A. Sensor's Data and System Faults

Performance is impacted by two major types of failures that wireless sensor nodes encounter. System problems are the first type. This kind occurs due to low battery conditions, hardware or connectivity issues, communication problems, or calibration [13]. The second category, data faults, includes substantial biased or unpredictable errors such outliers, noise, spikes, offset or gain, or stuck-at, when a sensor node functions correctly except for its sensing sample reading. If there is a high level of trust in the ground truth, a defect is often characterized as a deviation from the likely model of the occurrence.

### B. Mechanical Fault Detection Modern Techniques

In order to identify machine flaws, mechanical fault detection (MFD) uses machine learning algorithms. Over the last two or three decades, there has been a lot of interest in this method since it reduces the need for human involvement and allows for the autonomous identification of machine health statuses. Interestingly, review papers devoted to Reinforcement Learning (RL)-based methods in MFD are few [14][15]. The majority of current research articles do not go into RL; instead, they concentrate on supervised approaches and mention un/semi-supervised methods in passing.

### C. Types of Mechanical Faults

Many faults can interfere with the way mechanical systems work and remain dependable. Faults in the machinery can be noticed by sensors catching abnormal vibrations. Reporting the kind of fault as soon as possible helps with early diagnosis and maintenance. Among mechanical faults [16]. Common ones are called unbalance, misalignment and mechanical looseness, and their vibration patterns allow for correct detection. The initial harmonics of the motor rotation may be used to identify the majority of mechanical issues. The causes of vibration brought on by mechanical issues are improved as follows:

#### 1) Unbalance

Asymmetry in the motor's mass around the rotating axis owing to asymmetries, material flaws, and manufacturing flaws causes the motor to become unbalanced. Manufacturing a motor with perfect balance is nearly impossible. The motor's level of imbalance determines whether or not there is an issue. Every time the shaft rotates, the imbalance produces a periodic vibration signal of the same magnitude. The magnitude of the imbalance determines the vibration amplitude.

#### 2) Misalignments

They are causes of the degradation of machine parts that happen when two machines are connected. Misalignments can be either angular or parallel, and occasionally they combine the two. When the two machines' center positions diverge, angular misalignment occurs. significant multiple levels of rotation combined with angular misalignments are reflected in significant axial vibrations. When both axes should operate in parallel, parallel misalignment occurs. Radial vibration from twofold rotational speed is the predominant vibration. It may be horizontal or vertical. The higher-level vibration's direction indicates the misalignment direction.

#### 3) Mechanical Looseness

The basic structure of machines cannot move freely because of the way they are built. Movement between the surfaces may come from loose screws or deteriorating concrete, producing harmonic peaks in vibration that oscillate at the same frequency as the rotation. A very little residual misalignment brought on by mechanical looseness may result in excessive vibration levels. Depending on how the back slash affects the rotor and structure, the frequency spectrum may show misalignment, a deformed shaft, and/or imbalance. Early on, vibrations at one rotational frequency and its double frequency are caused by mechanical looseness. Fractional harmonics become more pronounced as the motor condition continues to deteriorate. Signals obtained while the machine is just lightly loaded show these harmonics the greatest.

## III. Sensor Data Technologies For Fault Detection

Hardware elements known as sensors are capable of recording various types of signals. Sensors can be used to gather data in various scenarios and are commonly found in everyday gadgets, such as smartphones, smartwatches, tablets, and specialized equipment like industrial and medical devices. One way to use sensor data is to measure some aspect of the environment around the sensor, such as chemical sensing, motion, touch, and proximity data, or picture or sound detection. The design of each system, the surroundings in which data are collected, and the specific features of the sensors chosen to carry out ADL identification all influence data gathering. Each sensor receives electrical impulses, which are measured and converted into a readable format by a module built into the mobile device to complete the data-collecting process [17].

### A. Types of Sensors

Sensors are essential to any application's automation because they detect changes in physical things by measuring and interpreting data. The sensing components and the corresponding electrical signal provide a measurable reaction whenever the physical condition for which a sensor is intended changes. components for sensing and the electrical signal they produce. Many types of sensors exist, ranging from very simple to quite complex. Sensors may be divided into groups based on their characteristics, conversion method, kind of material, physical phenomena they detect, characteristics they quantify, and field of application. Figure 1 shows many IoT sensor types, which are described below.

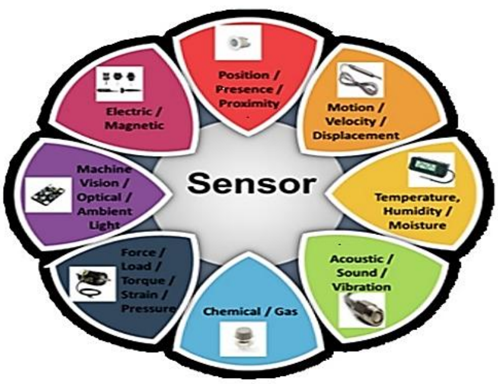


Fig. 1. Different types of IoT sensors

 

*1) Proximity Sensors*

It's easy to find the location of any nearby object without touching it thanks to a proximity sensor. By emitting electromagnetic radiation, such as infrared, it determines the existence of an item and then just monitors any changes in the return signal.

*2) Motion Sensors*

A motion detector is a device that recognizes every kinetic and physical movement in the environment. Using motion sensors, an application may watch residences while the homeowner is away. The server can receive images or movies when motion is detected.

*3) Temperature Sensors*

Temperature sensors measure heat energy, which is useful for identifying physical changes in the body. The authors employed temperature sensors to track the surrounding environmental parameters.

*4) Chemical Sensors*

Chemical sensors react by detecting any chemical reaction, chemical material, or combination of chemicals. Environmental events, building health, agricultural conditions, and other things may all be detected using this kind of sensor [18].

### *B. Optimal Sensor Placement for Fault Detection*

Properly positioning sensors helps ensure faults in mechanical systems are caught early and with more accuracy. Good placement makes sure all-important components are covered but data loss is minimized. In order to find the most useful places for the sensors, people rely on model-based optimization, measuring information entropy and using modal analysis. Example: Adding sensors to areas where stress and vibrations are common enables discovering problems early on. Advancements in advanced algorithms like genetic algorithms and machine learning mean sensors in complex systems can be set up without manual steps [19]. If emissions monitoring instruments are placed correctly, fault detection becomes more accurate and precise and overall maintenance expenses and downtime are minimized which also improves system availability.

### *C. Data Acquisition Techniques*

Systems rely on sensor data to find and fix problems in mechanical parts. Usually, industries select vibration, acoustic and temperature sensors depending on the fault being tested. The reliability of the data is significantly influenced by the proper placement and configuration of sensors, either individually or in groups [20]. Besides, having the right sampling rate, high resolution, and synchronized signals is essential for proper monitoring to prevent failures. Some of the data acquisition techniques are:

*1) Vibration Monitoring*

Vibration-based approaches are the most popular among the many condition monitoring techniques because they are easy to measure, dependable, and non-intrusive. For many years, vibration tracking has been used to find mechanical issues in instant messaging. When operating, radial magnetic forces that are proportional to the square of the flux density are generated between the rotor and stator surfaces. These forces cause vibrations in the motor frame, stator core, and winding. Vibration signals that are a result of the symmetrical air-gap and symmetrical components will vary when rotor, stator, and rolling bearing failures modify the machine's symmetry [21]. The majority of vibration measurements are often made using vibration-acceleration sensors, which employ the piezoelectric effect to function. The sensor's output voltage is determined by the force applied to it. To extract the important components and remove nonlinear effects caused by the cover frame and background noise, the vibration signals must be processed.

*2) Motor Current Signature Analysis (MCSA)*

The preceding mentioned approaches use either the transient or steady-state currents of the studied IM as data for MCSA. In several additional research, the steady-state current signature has been employed to diagnose IM defects. The fact that the current signature is greatly impacted by changes in load or speed is a significant drawback under steady-state conditions. In this situation, the spectra become hazy and traditional methods based on frequency analysis are ineffective. The restrictions can be addressed by analyzing the three-phase current signature of the IM in the transient regime. This is because low loads or no load are less likely to impact the current signal [22]. Since the initial current is seven to eight times greater than the steady-state current, the broken rotor bar fault will worsen the current variations even if a lesser IM is evaluated.

*3) Thermal Monitoring*

It is essential to have a solid understanding of the temperature of machine parts because of the thermal limitations of the insulations, coils, and other components of spinning electrical machines. Temperature measurement and thermal modelling are the two components of thermal monitoring for electrical equipment, and each has been briefly described [23]. A new wireless bearing temperature sensor was also introduced lately. This sensor detects changes in the magnetic field due to rising temperatures by combining a Hall Effect sensor with a ring-shaped permanent magnet.

## IV. ACCURACY AND TIMELINESS IN FAULT DETECTION

Fault detection works well when the results are both accurate and prompt. Reliable sensor readings make sure that problems are identified correctly, so there are not many false alarms. Prompt identification of problems means equipment can be repaired before parts break down and the system is disrupted. They work as a pair to help tweak maintenance actions and boost efficiency of mechanical equipment.

### *A. Ensuring Data Accuracy through Sensor Reliability*

The accuracy of diagnostic outcomes is directly impacted by feature extraction, the most crucial phase in fault diagnosis, which serves as the foundation for additional problem occurrence detection and fault type determination [24]. Feature extraction techniques change depending on the application environment for fault diagnostics. In machine condition monitoring, signal data is frequently utilized to extract features using signal analysis techniques. These techniques might be in the frequency domain, time domain, or a mix of both.

### *B. Improving Timeliness through Real-Time Fault Detection Systems*

The various implementation approaches are used to further categories RTFD methodologies, and their industrial uses are emphasized for analysis. Additionally, this section offers a thorough explanation of the RTFD procedure, including data gathering, preprocessing steps like dimensionality reduction or denoising, if required, as well as choosing the RTFD technique and how it operates.

### C. Balancing Accuracy and Timeliness in Fault Diagnosis

Both dependable and quick output are very important for proper functioning of fault detection systems, so a novel way to set adaptive thresholds in model-based systems has been developed. With this approach, uncertainties from the model and the surrounding environment are considered and optimal thresholds are chosen using statistical and information-theory tools as conditions change. By using this method, it is guaranteed that the system can better detect serious faults and reduce false alarms which enhances the system's reliability and efficiency in discovering issues.

## V. LITERATURE REVIEW

A survey of the literature on sensor data collection and defect detection methods for mechanical and mechatronic systems is included in this section, emphasizing synchronization, real-time monitoring, compression methods, and intelligent fault diagnosis. For clarity, a summary of the studied research is shown in Table I.

Fei and Junmei (2025) proposed a laboratory data acquisition and processing system based on intelligent sensor networks, seeking to increase experimental data acquisition's accuracy and efficiency. The system collects experimental data in real time by deploying distributed sensor nodes, and uses Huffman coding algorithm for data compression and transmission. Huffman coding effectively reduces the amount of data transmission by optimizing the coding length, thereby improving the transmission efficiency of the system and saving network bandwidth. To ensure the efficient operation of the system, this study designs a multi-level data processing algorithm based on intelligent sensor networks, which can quickly and accurately analyze and process data after data acquisition, thereby realizing efficient experimental data monitoring and control [25].

Wang, Lin and Cui (2024) focused on real-time data acquisition and monitoring technology in mechatronic systems, aiming to efficiently and accurately collect and process temperature and pressure data in the system, and to accomplish real-time system status monitoring by creating a sensible monitoring system architecture. This study establishes a reliable data acquisition system by applying temperature sensors and pressure sensors, combining data acquisition modules and RS-232 transmission methods. In terms of data processing, the moving average method is used to smooth the collected data, effectively removing noise and outliers, and ensuring the accuracy of the data [26].

Jawdeh, Li and Bazzi (2024) presented approach benefits from the use of a machine reference model-based phase locked loop to determine the actual rotor position and to detect position sensor faults. Once the fault is detected, control reconfiguration is proposed to switch from sensor-based control to sensor less control and ensure continuous operation. The new approach was tested in MATLAB/Simulink simulations as well as experimentally. Results show effective and fast position sensor fault detection. Moreover, the control reconfiguration successfully manages to maintain seamless motor operation with minimum disturbances [27].

Pothuri and Nagarajan (2024) introduced a novel Mechanical Fault Detection Network (MFD-Net) that enhances fault detection precision and efficiency in manufacturing environments. MFD- Net integrates advanced data preprocessing with a deep learning convolutional neural network (DLCNN) for effective feature extraction, paired with a machine learning-based Categorical Boosting (MLCB) classifier for optimal classification [28].

Malkani et al. (2023) focusing especially on WSN data collection. It explores several facets of query processing and data acquisition in WSNs and suggests an effective approach to data collecting that leverages the power of structured query language (SQL). In contrast to simulation-based evaluation, the proposed approach is verified on an actual sensor network testbed [29].

Guangyue et al. (2022) Synchronisation of the multi-sensor array is a crucial element in the measuring of temperature gradients. This study addressed the problem of synchronisation in space temperature gradient measurement by presenting a distributed parallel data gathering method based on a single bus temperature sensor. A single-point temperature measurement device for arrays is the DS18B20 single bus temperature sensor. Prior to beginning the lengthy procedure, ID matching is completed, and then all IDs' temperature conversion is initiated [30].

Table I presents a summary of the literature review, highlighting each study's focus on sensor data acquisition and fault detection, the methods used, key outcomes in accuracy and efficiency, identified limitations, and suggested improvements for future research.

TABLE I. COMPARATIVE ANALYSIS OF REVIEWED STUDY BASED ON SENSOR DATA ACQUISITION AND FAULT DETECTION

| Reference | Study On | Approach | Key Findings | Challenges | Future Direction |
|---|---|---|---|---|---|
| Fei and Junmei (2025) | Intelligent sensor-based lab data acquisition system | Distributed sensor network with Huffman coding and multi-level data processing | Enhanced transmission efficiency and accurate experimental data processing | Network complexity, coding efficiency vs. processing load | Optimize coding and processing algorithms, implement in real-time lab environments |
| Wang, Lin and Cui, (2024) | Real-time temperature and pressure monitoring in mechatronic systems | Combination of temperature & pressure sensors, RS-232 communication, moving average for noise filtering | Real-time data acquisition and noise-free processing ensures accurate monitoring | Handling real-time constraints, limited transmission speed | Incorporate advanced filtering algorithms, integrate with IoT for remote monitoring |
| Jawdeh, Li and Bazzi (2024) | Position sensor fault detection and control reconfiguration | Machine reference model-based PLL, sensor less control upon fault detection | Fast and effective fault detection, seamless control switch maintaining motor operation | Sensor transition without delay, maintaining accuracy | Apply to diverse motor types, explore real-time hardware integration |
| Pothuri and Nagarajan (2024) | Mechanical fault detection in manufacturing | MFD-Net combining DLCNN with MLCB classifier | High accuracy in mechanical fault detection and classification | Data quality, model training complexity | Extend to multi-class fault detection, adapt to real-time applications |

| | | | | | |
|---|---|---|---|---|---|
| Malkani et al. (2023) | Acquisition and inquiry of data in WSNs | SQL-based data acquisition on real-world WSN testbed | Validated SQL-based approach enhances query processing and acquisition | Resource constraints in WSNs, query complexity | Develop lightweight query languages, optimize for large-scale WSNs |
| Guangyue et al. (2022) | Temperature gradient measurement synchronization | Distributed parallel data acquisition using DS18B20 single bus sensors and ID matching | Achieves synchronization in temperature measurements by initiating all sensor conversions simultaneously | Synchronizing multiple sensors on a single bus, latency in conversion | Improve synchronization algorithms, scalability to larger sensor arrays |

## VI. Conclusion and Future Work

Maintaining the effectiveness and dependability of mechanical systems, particularly in demanding industrial settings, depends heavily on sensor data collection and problem detection. This review explored various techniques and studies emphasizing synchronization, real-time data monitoring, and the integration of intelligent algorithms for enhanced fault detection. Advanced sensor networks, noise filtering techniques, and Models based on adaptive machine learning have demonstrated potential in improving the timeliness and accuracy of fault detection systems. However, challenges remain, such as data noise, synchronization delays, and computational limitations in real-time processing, hindering the full potential of these technologies in complex industrial setups. Enhancing the scalability and adaptability of data collecting systems should be the goal of future research, particularly in environments involving large sensor networks or real-time operations. The development of lightweight compression and transmission algorithms will also help optimize performance in bandwidth-constrained conditions. Moreover, integrating reinforcement learning and hybrid AI models into fault detection pipelines could provide better generalization across diverse machinery and fault types. There is also a need to enhance fault-tolerant designs for sensors themselves, ensuring consistent performance even in the presence of partial hardware failures. Advancements in these areas will significantly boost predictive maintenance capabilities and operational safety in modern industrial systems.

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