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| **RESEARCH ARTICLE**

A Review of Sensor Data Acquisition Methods for Accurate and Timely Detection of Faults in Mechanical Systems

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| ABSTRACT
The fault detection of mechanical systems is essential to the reliability of such systems in the industrial environment and it is enabled by the efficient method of sensor data acquisition. This review research studies the importance of different sensors and acquisition techniques to detect defects of mechanical parts with reference to current developments and applications. The paper identifies some of the important sensor types including temperature, motion, proximity, and chemical sensors and discusses the application of these sensors in real-time monitoring and diagnostics. More emphasis is put on the contemporary techniques of data acquisition such as synchronization, signal preprocessing, and smart systems, which are able to improve the accuracy of decision-making. It also examines how machine learning and deep learning models can be integrated into fault detection models that enhance efficiency and minimize the need to rely on manual inspection in diagnostic procedures. The review also provides the comparative results of recent open-access research to assess the strengths, issues, and opportunities of the future. The significance of the accuracy and timeliness is described with references to the impact of the late or wrongful detection on the productivity and safety of industry. In general, the review can be considered as a reference point for researchers and engineers who are interested in creating or enhancing sensor-based fault detection systems in mechanical systems.

| KEYWORDS
Sensor Data Acquisition, Fault Detection, Mechanical Systems, Real-Time Monitoring, Machine Learning, Industrial Diagnostics, Accuracy, Timeliness

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1. Introduction

Mechanical machinery is an essential part of industrial activities. They are therefore essential to the production and manufacturing processes. Because of their important role in the manufacturing line, they are often placed in difficult environments, leaving them susceptible to a range of mistakes and malfunctions. In complex sensor systems, faults may be characterized as unforeseen occurrences that could happen at a certain moment, which could lead to more significant events or a sequence of unforeseen events[1].

Sensors are frequently employed to gather data and signals, particularly in the fields of agriculture, aquaculture, disease detection, machinery monitoring, and environmental monitoring. Multi-sensor information fusion technology is becoming more and more necessary for intelligent systems as science and technology progress; it is becoming a more significant factor in the detection of industrial machinery and equipment faults[2]. In the majority of intricate industrial settings, a single sensor is employed to get a particular useful piece of data from the mechanical apparatus.

The specifics of data collection may change based on the kinds of behaviours that are being examined in the study. For instance, a waist sensor with a modest sample rate could be adequate to identify basic actions (i.e., coarse granularity) like sitting and walking. A single waist-worn sensor might not be enough to identify combinatorial events with greater granularity, such as eating and driving[3]. It is crucial to identify activities of daily living (ADL) accurately and promptly in order to instill confidence and security in the elderly. If you don't, there might be major consequences, especially in an emergency like a fall.

The signal that asset monitoring sensors provide. Timeliness and precision in the data collected by sensors and processed by algorithms are necessary for evidence-based, informed decision-making. However, if sensors—which are also impacted by malfunctions—have captured inaccurate data, algorithms may be impacted by inaccurate categorization and interpretation[4]. The selected maintenance plan is then directly and indirectly impacted by accuracy. 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 Fundamentals of Fault Detection in Mechanical Systems. Section III covers sensor data technologies for fault detection. 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.

2. Fundamentals of Fault Detection In Mechanical Systems

In dependable mechanical systems, fault diagnosis and detection are critical issues. 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[5]. Actuators such as gearboxes, hydraulic valves, ball screws, etc. are frequently utilized in mechanical transmission systems. For example, in a conventional mechanical transmission system, a gearbox typically drives the load. A servomotor then drives the gearbox.

B. Sensors Data and System Faults

Performance is impacted by two major types of failures that wireless sensor nodes encounter. System problems are the first type. Low battery life, issues with hardware or connections, calibration issues, or communication problems are the causes of this kind[6]. The second category, data faults, includes significantly biased or random errors such as stuck-at, offset or gain, noise, spikes, or outliers, when a sensor node operates flawlessly aside from its sensing sample reading. If there is a high degree of trust in the ground truth, a defect is often characterized as a deviation from the likely model of the occurrence.

C. Mechanical Fault Detection Modern Techniques

Mechanical Fault Detection (MFD) uses machine learning approaches to find machine issues. Over the past two or three decades, there has been a lot of interest in this method since it reduces the need for human involvement and allows autonomous detection of machine health conditions. Interestingly, review publications devoted to Reinforcement Learning (RL)-based methods in MFD are few[7]. The majority of current research articles do not go into RL; instead, they concentrate on supervised approaches and mention un/semi-supervised approaches in passing.

D. 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, common ones are called unbalance, misalignment and mechanical looseness and their vibration patterns allow for correct detection. The initial harmonics of the motor rotation help identify the majority of mechanical issues. The sources of vibration caused by mechanical issues are then increased.

1) Unbalance

Asymmetry in the mass of the motor around the spinning axis due to material defects and asymmetries, and manufacturing flaws causes the motor to become unbalanced. Making a motor that is precisely balanced is nearly impossible. Whether or not there is an issue depends on how much the motor is affected by an imbalance. Every time the shaft rotates, the imbalance produces a periodic vibration signal of the same magnitude. The imbalance's size determines the vibration's amplitude.

2) Misalignments

These are the reasons why machine parts deteriorate when two machines are connected. Misalignments come in two flavours: parallel and angular, and occasionally both. When the two machines' center positions are not in agreement, angular misalignment occurs. High rotational levels combined with angular misalignments are indicated by elevated axial vibrations. When both axes are supposed to function in parallel, parallel misalignment occurs. The radial vibration caused by twofold rotational speed is the predominant one. Both vertical and horizontal are possible. The direction of the higher-level vibration indicates the misalignment.

3) Mechanical Looseness

The underlying structure of machines is built in a way that prevents it from moving freely. Regardless of whether screws come loose or the concrete foundation deteriorates, movement may result in vibrational harmonic peaks oscillating at the same rotational frequency between the surfaces. Relatively minor residual misalignment brought on by mechanical looseness might result in significant vibrations. Depending on how the rotor and structure are affected by the backslash, the frequency spectrum may show misalignment, warped shaft, or imbalance. Early on, mechanical looseness results in vibrations at both the single and double rotational frequencies. An increase in the amplitude of fractional harmonics is the result of further motor condition degradation[8]. When the machine is just lightly loaded, these harmonics are most noticeable in the signals.

3. Sensor Data Technologies for Fault Detection

Hardware elements with the capacity to record various signal kinds are called sensors. Sensors are found in many everyday gadgets, such as tablets, smartphones, wearables, and specialized equipment, such as industrial and medical gadgets. They can be used to gather data in a variety of scenarios. The measurement of certain environmental properties, such as acoustic or visual detection, motion, touch, chemical sensing, and proximity data, is an example of how sensor data is used[9]. The specific features of the sensors chosen to identify ADLs, the settings in which data is collected, and the design of each system all affect data gathering. A module included inside the mobile device handles the data collection procedure, which entails measuring and transforming each sensor's electrical impulses into a readable format.

E. Types of Sensors

Sensors are essential to every application's automation since they measure and analyze data to detect changes in tangible things. In response to changes in the physical conditions for which it is intended, a sensor produces an electrical signal and a measured responsive sensing element. electrical signal corresponding to the items that are being sensed. There are many different kinds of sensors, and they range in complexity from the basic to extremely sophisticated[10]. The specifications, conversion technique, material type, physical events being detected, attributes being measured, and application field may all be used to classify sensors. Figure 1 shows many IoT sensor types, which are described below:

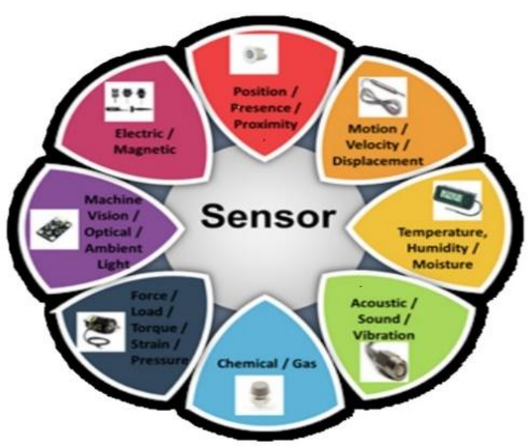

Fig. 1. Different types of IoT sensors

1) Proximity Sensors

It is easy to locate any nearby object without coming into contact with it, thanks to a proximity sensor. It searches for changes in the return signal after detecting the presence of an object using electromagnetic radiation, such as infrared.

2) Motion Sensors

An apparatus that can detect any kinetic or physical movement in the surroundings is called a motion detector. Motion sensors might be used by an app that keeps an eye on houses while the owners are away. Image or movies can be transmitted to the server when motion is detected.

3) Temperature Sensors

Temperature sensors, which measure heat energy, are useful in recognizing bodily changes. To monitor the environment in the immediate vicinity, the authors employed temperature sensors.

4) Chemical Sensors

Chemical sensors respond by identifying any chemical item, chemical reaction, or mixture of chemicals. These sensors can be used to detect building health, agricultural conditions, environmental events, and other things.

F. 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.[11] 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.

G. 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. Correct installation and arrangement of sensors, either single or in groups, strongly determine how reliable the data. 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 monitoring has been used to find mechanical issues in IM[12]. In operating mode, the square of the magnetic forces generated radially between the stator and rotor surfaces is determined by the flux density. Vibrations of the motor frame, windings, and stator core are caused by these forces. When the machine's symmetry is altered by rotor, stator, and rolling bearing problems, vibration signals that depend on the symmetrical air-gap and symmetrical components also change.

2) Motor Current Signature Analysis (MCSA)

The preceding methods use either the analysed IM's transient or steady-state currents as MCSA data. Several additional investigations have used the steady-state current signature to detect IM faults[13]. The current signature is greatly impacted by changes in load or speed under steady-state conditions, which is a significant drawback. In this situation, traditional frequency-analysis-based methods are ineffective because the spectra become hazy. Analyzing the IM's three-phase current signature in the transient domain can help overcome these restrictions.

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. The two components of thermal monitoring for electrical equipment are temperature measurement and thermal modelling, both of which have been briefly described[14] A novel wireless sensor for monitoring bearing temperature was also introduced lately. This sensor uses a combination of a Hall Effect sensor and a ring-shaped permanent magnet to detect changes in the magnetic field caused by rising temperatures.

4. 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 the efficiency of mechanical equipment.

H. Ensuring Data Accuracy through Sensor Reliability

Feature extraction, the most crucial stage in fault diagnosis, serves as the foundation for additional problem occurrence detection and fault type identification, both of which have a direct impact on the precision of diagnosis outcomes. Distinct fault diagnostic application settings need distinct feature extraction techniques. Signal analysis techniques, which may be in either the time domain, the frequency domain, or simultaneously, are typically used to extract characteristics in machine status monitoring based on signal data.

I. Improving Timeliness through Real-Time Fault Detection Systems

RTFD techniques are further classified according to the various implementation techniques, and their industrial uses are emphasized for examination[15]. This section also goes into great length on the RTFD process, covering data collection, pre-processing steps like denoising or dimensionality reduction if needed, and the choice and operation of the RTFD technique.

J. Balancing Accuracy and Timeliness in Fault Diagnosis

Both dependable and quick output are very important for the 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.

5. Literature Review

This section presents a literature review on sensor data acquisition and fault detection techniques in mechanical and mechatronic systems, emphasizing synchronization, real-time monitoring, compression methods, and intelligent fault diagnosis.

Jia, Liu and Li (2019) examines the issue of detecting faults in the ammunition fuze assembly system's high-risk operation and talks about a technique based on the sliding mode observer. Initially, a dynamic model of the manipulator is created, and its dynamic characteristics are provided. The defect detection approach is then achieved when the sliding mode observer equation is suggested and the uncertain section is approximated using an RBF neural network. Last but not least, the double joint manipulator simulation confirms the algorithm's efficacy[16].

Tao et al. (2019) To find and diagnose power switch problems in WPGSs' grid-connected converters, a unique signal processing-based method is suggested. This method is entirely distinct from the current-based methods now in use. The instantaneous amplitudes of the three-phase output current may be computed online using the suggested weighted sliding Hilbert transform (WSHT) method without the boundary problem interfering. Lastly, simulation findings show that the grid-connected converters can handle open-circuit failures[17].

Xin, WANG and LI (2018) offer a unique defect detection method based on neural networks that a class of nonlinear systems may benefit from its utilization. The adaptive observer used a single hidden-layer feed-forward wavelet neural network for defect detection. The network weights are updated using a modified back-propagation technique to guarantee network convergence, and stability is provided via the Lyapunov function[18].

Zhu et al. (2018) The frequency analysis technique is used to explore the detection of nonlinear rotor-bearing system problems. To determine the faulty bearing conditions, the Nonlinear Output Frequency Response Functions (NOFRFs) of the nonlinear rotor-bearing system are assessed. The use of the NOFRFs-based fault detection system is demonstrated through simulation and experimental investigations. The findings show that the higher order NOFRFs are vulnerable to bearing issues and are unaffected by the rotor's imbalance distance[19].

Shang et al. (2017) emphasizes the investigation of mechanical vibration faults. The study presents typical mechanical fault kinds and fault mechanisms based on acoustic signals; It uses the whole sound recording technology to extract various mechanical failure data in the field; the signal is then examined in the frequency, temporal, and inverse frequency domains, and the guidelines governing the various defects' acoustic characteristics are collected; Ultimately, the system's software and general components are created, and the human-computer interface, Included are a software flow chart and a system architecture diagram[20].

Lan and Patton (2016) This study proposes an approach that combines fault estimation and fault-tolerant control (FTC) for interconnected linear systems with unpredictable nonlinear interactions that are susceptible to unknown, limited sensor failures. Making use of the concurrently provided state/fault estimations by a decentralized unknown input observer, a decentralized FTC approach is applied to correct for sensor fault effects and preserve the system's overall strong stability. A single-step linear matrix inequality (LMI) method is used to jointly solve the observer and controller gains[21].

A summary of the literature review is provided in Table I, emphasizing the emphasis on sensor data collection and defect detection in each research, the methods used, key outcomes in accuracy and efficiency, identified limitations, and suggested improvements for future research.

TABLE I. COMPARATIVE ANALYSIS OF LITERATURE REVIEW BASED ON SENSOR DATA AND FAULT DETECTION IN MECHANICAL SYSTEMS

Reference	Study On	Approach	Key Findings	Challenges	Future Direction
Jia, Liu & Li (2019)	Fault detection in high-risk ammunition fuze assembly system (double-joint manipulator)	Sliding Mode Observer (SMO) with RBF Neural Network for uncertainty approximation	Proposed SMO-based RBF method effectively detects faults in nonlinear manipulator systems; validated via simulations	Sensitivity to model uncertainties; real-time application complexity; dependence on accurate dynamic modelling	Extend to real-world experiments; improve robustness against noise; integrate adaptive learning components for online updates
Tao et al. (2019)	Power switch failure detection in Wind Power Generation Systems (WPGSs) grid-connected converters	Instantaneous amplitude estimate using the Weighted Sliding Hilbert Transform (WSHT)	WSHT accurately detects and locates open-circuit faults without boundary effects; simulation confirms strong performance	Algorithm may face challenges under high noise or dynamic grid conditions; real-time deployment constraints	Hardware implementation; enhanced fault classification; integration with intelligent control for self-healing WPGSs
Xin, Wang & Li (2018)	Fault detection in nonlinear systems	Adaptive observer using Wavelet Neural Network (WNN) with modified backpropagation & Lyapunov stability	Designed WNN-based observer ensures convergence and stability; effective for nonlinear dynamics	Computational complexity; training stability; sensitivity to initial weight selection	Develop faster learning algorithms; extend to multi-fault scenarios; apply to high-dimensional nonlinear systems
Zhu et al. (2018)	Nonlinear rotor-bearing system fault diagnostics	Frequency analysis using Nonlinear Output Frequency Response Functions (NOFRFs)	Higher-level Experiments have confirmed that NOFRFs are extremely sensitive to bearing failures and insensitive to rotor imbalance	Requires high-quality vibration signal; computational cost of higher-order frequency responses	Real-time NOFRF computation; application to multi-fault rotor systems; integration with machine learning classifiers
Shang et al. (2017)	Mechanical vibration fault diagnosis using acoustic signals	Time-domain, frequency-domain & inverse-frequency analysis; development of fault diagnostic software system	Acoustic patterns of different faults successfully identified; provided a complete acquisition-analysis-diagnosis framework	Acoustic signals affected by ambient noise; generalization across machines remains difficult	Advanced filtering; machine-learning-based acoustic classification; deployment in industrial IoT vibration monitoring
Lan & Patton (2016)	In linked linear systems with unpredictable nonlinear interactions, fault estimation and fault-tolerant control	Decentralized Unknown Input Observer + LMI-based FTC design	Achieves robust stability and compensates sensor faults effectively; integrated estimation–control framework	LMI complexity for large systems; assumptions of bounded nonlinearities; observer design scalability	Apply to large-scale cyber-physical systems; incorporate adaptive/learning-based FTC; enhance resilience against actuator faults

6. Conclusion and Future Work

Particularly in challenging industrial environments, sensor data collection and fault detection are essential to preserving the effectiveness and dependability of mechanical systems. Data-gathering of sensors and fault detection in mechanical systems are significant to ensure the efficiency and reliability of the mechanical systems, particularly in a severe industrial environment. This review discussed different methods and research with the focus on synchronization, continuous data observation, and incorporation of smart algorithms to achieve a high fault detection level. There has been an indication that advanced sensor networks, noise filtering schemes and adaptive machine learning-based models can enhance the accuracy and timeliness of fault detection systems. There is still, however, issues like data noise, delays in synchronization, and high-performance limitations that exist in real-time processing, which limit the full capabilities of these technologies in complicated industrial configurations.

Future research should focus on enhancing data acquisition systems' scalability and flexibility, particularly in environments involving large sensor networks or real-time operations. Algorithms of lightweight compression and transmission will also help in optimization of performance in light bandwidth conditions. Furthermore, incorporating reinforcement learning and hybrid AI models into fault detection pipelines may be more generalized to a variety of machinery and types of faults. Fault-tolerant designs of sensors themselves also require improvement, so that they can maintain their expected performance even when there are partial hardware failures. The innovation of these spheres will enhance predictive maintenance and the safety of functioning of contemporary industrial systems considerably.

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