



SYNERGIZING SMART SENSORS AND ARTIFICIAL INTELLIGENCE FOR MAINTENANCE 4.0: A CRITICAL REVIEW AND FUTURE PARADIGMS

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ABSTRACT

Various industrial equipment relies on complex mechanisms to maintain high production efficiency and consistent product quality. However, frequent equipment failures and maintenance issues caused by mechanical wear can lead to costly downtime, also quality fluctuations. Traditional maintenance methods such as preventive or reactive maintenance, often fail to predict failures accurately, resulting in ineffective strategies. The integration of smart sensor technologies is revolutionizing maintenance and repair of various equipment. These sensors continuously analyse equipment parameters such as temperature, vibration, pressure, and humidity. The aim of using sensors is to provide real-time monitoring, predictive maintenance, and fault detection. Using the Internet of Things (IoT) and Artificial Intelligence (AI), sensors increase operational efficiency, reduce maintenance costs, and extend lifespan. This study explores the key components, sensor types, predictive maintenance approaches, advantages, drawbacks, and future trends.



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I. INTRODUCTION

In the era of Industry 4.0, the maintenance paradigm is undergoing a fundamental transformation. In a highly automated manufacturing environment, traditional approaches such as reactive maintenance and preventive maintenance (PPM) are no longer sufficient to meet the requirements of cost efficiency and operational reliability. The main problem of these strategies remains the high probability of either sudden failures or excessive costs for replacing healthy components. The transition to intelligent maintenance (Maintenance 4.0) has been made possible thanks to the synergy of the Industrial Internet of Things (IIoT) and advanced predictive analytics. At the heart of this ecosystem are smart sensor technologies that act as the “sense organs” of digital manufacturing. However, despite the rapid growth of the sensor market, there is still no system synthesis in the academic literature that would link the physical parameters of sensors with specific algorithmic solutions for predicting the condition of equipment. This article provides a critical review of the current state and development prospects of maintenance strategies in a digital industrial environment. Unlike descriptive studies, this review focuses on an analytical comparison of different sensor types and their role in AI-based decision-making architectures. The study is designed not only to present the current technology set, but also to identify critical gaps in existing monitoring methods. This approach allows for a holistic understanding of how smart data can be transformed into a strategic advantage for the enterprise and ensures the long-term sustainability of production processes.

II. SYSTEMATIC REVIEW METHODOLOGY

To ensure scientific objectivity and depth of analysis, a systematic literature review method was used in this study. The research process was structured in accordance with international standards for the analysis of scientific data, which allowed for the synthesis of technological and managerial aspects of maintenance in the era of Industry 4.0.

II.1 SEARCH STRATEGY AND DATA SOURCES

A search for relevant publications was conducted in the leading bibliographic databases: Scopus, Web of Science, IEEE Xplore, ScienceDirect and MDPI. The keyword combinations used were: "Smart Sensors", "Industry 4.0", "Predictive Maintenance", "Machine Learning in PdM", "Confectionary industry" and "Internet of Things (IoT)".

II.2 SELECTION AND FILTERING CRITERIA

The research corpus was compiled based on Strict Inclusion Criteria:

Activity: Special attention was paid to articles published between 2020 and 2026, which account for more than 50% of the total reference list. This allowed us to integrate the latest advances in additive manufacturing of sensors [1] and modern diagnostic methods [2], [3] into the review.

Thematic activity: The community included articles covering the entire value chain, from the physical principles of sensor operation (for example, temperature [1], [4], [5], vibration [6], infrared [7] and piezoelectric [8]) to complex analytical systems based on artificial intelligence [9], [10].

Industry focus: Examples from the food industry [11-15] and building management systems [16] were analyzed to increase practical relevance.

II.3 SYNTHESIS AND CLASSIFICATION DATA

The 56 sources selected in the final stage were classified into three main areas:

- Hardware level: Smart sensor technologies and communication protocols [17], [18].
- Analytical level: Machine learning methods and neural networks for remaining useful life prediction (RUL) [10], [19].
- Strategic level: Moving from reactive models to predictive and reliability-oriented maintenance (RCM) [11], [14].

Systematization of the selected literature allowed not only to classify sensor types but also to conduct a critical cross-analysis of their application in various industrial scenarios. During data synthesis, special attention was paid to identifying technological gaps between theoretical models and practical constraints of Industry 4.0. Figure 1 clearly shows the literature filtering process, which ensures that more than 50% of the analyzed articles reflect the most relevant scientific advances for 2020–2026.

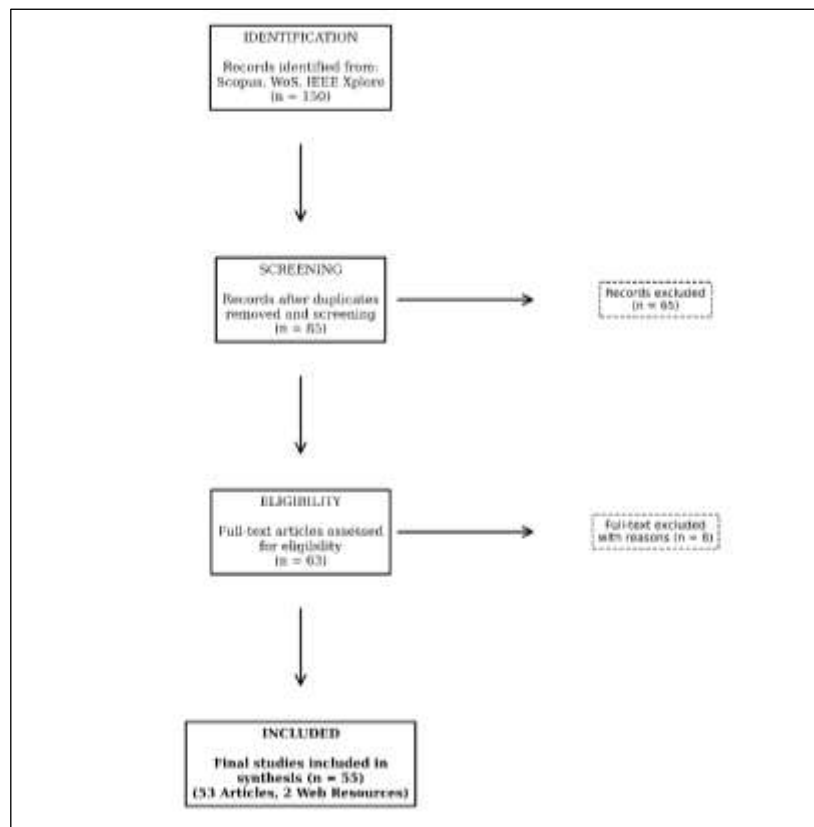


Figure 1: Flow diagram of review selection.

Source: Authors, (2026).

Based on the presented selection process, the final list of sources was structured to identify the most effective hardware solutions. A critical analysis of the selected literature shows that the effectiveness of predictive maintenance systems directly depends not only on the algorithmic basis, but also on the physical characteristics of the primary transducers. Therefore, the main types of smart sensors, their accuracy characteristics and limitations in industrial operation are discussed below.

III. ANALYTICAL OVERVIEW OF SMART SENSOR SYSTEMS

III.1 SMART SENSOR CONCEPT

Smart sensor systems are essential for ensuring safety and monitoring health status. A smart sensor typically combines sensing element with a microprocessor that processes the data and provides informative outputs to user. These systems are modular - they include input, data processing, independent power, and the ability to transmit or display information. The basic idea behind smart sensors is to integrate microprocessors with sensor technology to provide interpretive power and improve performance. The functionality of smart sensors consists of several layers: signal detection from sensors, signal processing, data validation, and data transmission. The microprocessor is coupled with the sensing elements to provide excitation, signal conditioning, and data logging. The data acquisition layer converts analog signals to digital signals, as well as compensating for factors such as thermal drift. The intelligence embedded within the system continuously monitors the sensors, validates the data, and checks sensor calibration for ensuring reliable data output. Smart sensors can perform internal processing by providing functions such as self-calibration, self-health assessment, and compensated measurements. This built-in intelligence allows system to assess the health and reliability of data, ultimately optimizing the sensor's performance. These systems can also network with other sensors to share data for better situational awareness. Such networking increases reliability by eliminating unnecessary data inputs and simplifies communication between the sensors themselves or with central hub. Research in this area aims to develop sensors that deliver the necessary information for informed decision-making, which can be applied across a wide range of industries, from security to environmental monitoring. The future of smart sensor systems focuses on improving adaptability, automation, and data exchange capabilities to meet diverse application needs. Figure 2 explains this system and working principle [20].

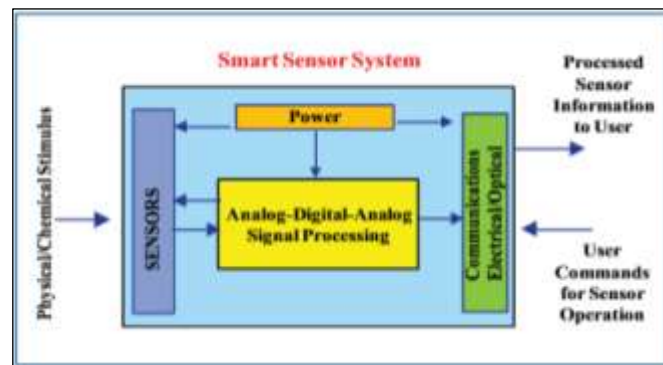


Figure 2: Smart sensor system explanation.
Source: [20].

Key components of smart sensor systems. Smart sensors are systems that consist of several integrated components to provide advanced monitoring and diagnostic capabilities. These components work together to collect information from the environment and convert it into a form suitable for processing.

Transducer. A transducer is an electrical device that converts one form of energy into another and plays a crucial role in the operation of smart sensors. Simply put, it converts physical quantities into measurable electrical signals. It is because of this property that transducers are widely used in sensor technologies. Transducers can operate on various types of energy. These include mechanical, electrical, light, chemical, thermal, acoustic, and electromagnetic energy. Figure 3 shows a general representation of the main elements of transducers, but the structure of these elements may vary in real applications. Transducers are particularly important in smart sensor applications. They detect and measure environmental parameters such as temperature, pressure, vibration, and humidity. The accuracy of these measurements directly affects the reliability of the overall sensor system.

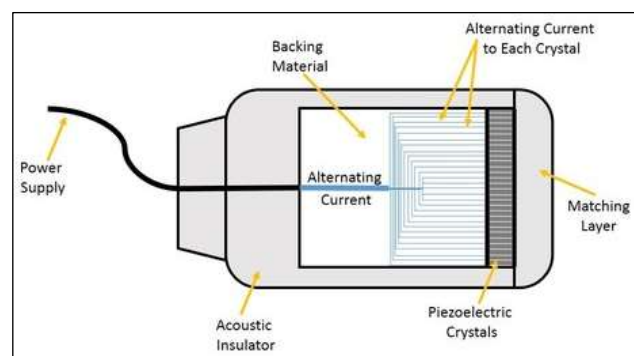


Figure 3: Transducer's basic elements.
Source: Author, (2026).

Basic components of transducers. A transducer is basically made up of two main components. The first is the sensing element. This part detects a physical quantity or how that quantity changes over time and responds accordingly. The other component is the transmitting element. Its job is to convert the output from the sensing element into a proportional electrical signal. In general, the job of a transducer is to sense an incoming form of energy and convert it into another, usually electrical, form. This property or condition, which is converted into an electrical signal, is considered the measured quantity. Although this process seems simple, it can be quite complex in practical applications. In some cases, a transducer performs both the sensing and transmitting functions at the same time. A thermocouple is a good example of this. Thus, the temperature difference that occurs at the junction of two dissimilar metals produces a voltage proportional to the temperature, eliminating the need for an additional transmitting element.

Classification of transducers. Transducers can be classified according to several criteria. These include the method of energy conversion, the type of output signal, and the electrical principles used [21]. According to the energy conversion, transducers are divided into two groups. Active transducers generate an electrical signal corresponding to a physical input without requiring an external energy source. Piezoelectric sensors and thermocouples are included in this group. Passive transducers require an additional energy source to operate. They mainly generate changes in passive electrical quantities. Thermistors and potentiometers are examples of this. Transducers are also distinguished based on the output signal. Analog transducers convert the input signal into a continuous output function. Voltmeters, linearly variable differential transformers (LVDTs), thermocouples, and thermistors belong to this group. Digital transducers, on the other hand, present the output in the form of discrete pulses or signals. Optical sensors, light sources, and photocells are examples of this. According to their functional characteristics, transducers are divided into two types: primary and secondary. Primary transducers convert a physical quantity directly into a mechanical signal. A thermistor is a simple example of this. Secondary transducers convert mechanical signals into corresponding electrical signals. Bourdon tube pressure sensors are included in this group.

Applications of transducers. Transducers are widely used in various fields and form the basis of many technological processes. In industrial automation, they play an important role in monitoring the condition of machines, pressure, temperature and vibration. In general, the application of transducer technologies allows for real-time data analysis in industry and other fields. This allows for increased efficiency, improved safety, and more optimal resource management. Table 1 summarizes various transducers, their functions, operating principles, input and output parameters, and practical applications.

Table 1: Overview of various transducers and their functions.

Type	Purpose	Principle	Input	Output	Applications
Thermocouple	Temperature measurement	Generates voltage based on temperature difference at junction of two metals [22]	Heat (Temperature)	Voltage (mV)	Industrial furnaces, food processing, HVAC systems
Thermistor	Temperature sensing	Resistance changes with temperature variations [23]	Heat (Temperature)	Change in resistance	Medical devices, automotive temperature control
Piezoelectric sensor	Pressure and vibration detection	Generates voltage when subjected to mechanical stress [24]	Force, Pressure, Vibration	Electrical voltage (mV)	Structural health monitoring, accelerometers
Optical sensor	Object sensing	Detects intensity or interruption of light [25]	Light (Photons)	Electrical signal	Barcode scanners, optical fiber communication
Potentiometer	Position and displacement sensing	Varying resistance changes voltage output [26]	Mechanical position	Voltage output	Audio control, joystick positioning, robotics
Capacitive sensor	Proximity and humidity sensing	Measures capacitance variation due to object proximity or moisture content [27]	Distance, Humidity	Electrical capacitance	Touchscreens, humidity control systems
Ultrasonic sensor	Distance measurement and object detection	Emits ultrasonic waves and measures reflection time [28]	Sound Waves (Ultrasonic)	Time delay / Voltage	Level monitoring, parking sensors, robotics
Hall effect sensor	Magnetic field detection	Measures voltage changes in response to magnetic field variations [29]	Magnetic field	Voltage signal	Motor speed sensing, proximity detection
Strain gauge	Stress and strain measurement	Resistance changes with applied force or strain [30]	Mechanical strain	Change in resistance	Bridges, aircraft structures, load cells

Source: Authors, (2026).

Transducer parameters directly determine the overall performance of the transducer. These parameters indicate how reliable and accurate it works. One of the most important indicators is sensitivity. Sensitivity indicates how much output the transducer can generate in response to a certain change in the input. Another important parameter is hysteresis. Hysteresis is related to the fact that the transducer maintains the same output value regardless of the increase or decrease in the input signal. In practice, this property is considered important to ensure the stability of measurements. The range indicates the lowest and highest values that the transducer can measure. The span is simply the difference between these two values. Sometimes these concepts are confused, but they are functionally different.

Linearity describes how well the output signal is proportional to the input changes and has a significant impact on the accuracy of the measurement. In addition to these, there are other parameters that affect the overall performance of the transducer. Accuracy, resolution, and response time are particularly important in this regard and are often taken into account in real applications. Although the terms sensor and transducer are often used interchangeably, there are some differences between them. A sensor is a device that detects and responds to changes in physical phenomena, such as temperature, pressure, or light. Its output can be converted to another form, but this conversion does not always occur. A transducer, on the other hand, has a broader function. It not only senses a physical parameter, but also converts that parameter from one form of energy to another. It is this feature that distinguishes a transmitter from a sensor. For example, a conventional thermometer is considered a sensor because it detects temperature changes but does not convert energy to another form. A thermocouple, on the other hand, both senses temperature and converts it into an electrical signal. Therefore, a thermocouple is considered a transmitter. In general, almost all transmitters perform the function of a sensor. However, it would not be correct to call all sensors transmitters unless they perform energy conversion.

III.2 TYPES OF SMART SENSORS USED IN INDUSTRY

Smart factories are built on intelligent machines, devices, and control systems that can continuously monitor key parameters of production processes. This approach has significantly changed the traditional working principles of factories. Machines can now communicate more accurately with each other, and in many cases, need for human intervention is minimized. At the same time, the level of performance expected from the systems has also increased. As a result, the demand for reliable and stable sensor systems has increased significantly.

Basic elements of sensors. The structure of a smart sensor depends on the purpose for which it is used. However, most smart sensors have three main components: the sensor element, the microprocessor unit (MPU), and the communication module. Each of these parts performs its function, and if a problem occurs in one of them, the overall operation of the sensor is also negatively affected. A simplified schematic representation of smart sensors is shown in Figure 4.

Sensing element. The sensor element is the part of the sensor that is in direct contact with the environment. It detects physical phenomena such as temperature, humidity, or pressure and converts this information into an analog signal [31]. In some applications, several sensor elements can be placed within a single sensor. This allows for the parallel measurement of several parameters with the same device. The analog signal received from the sensor element is transmitted to the microprocessor unit for further processing.

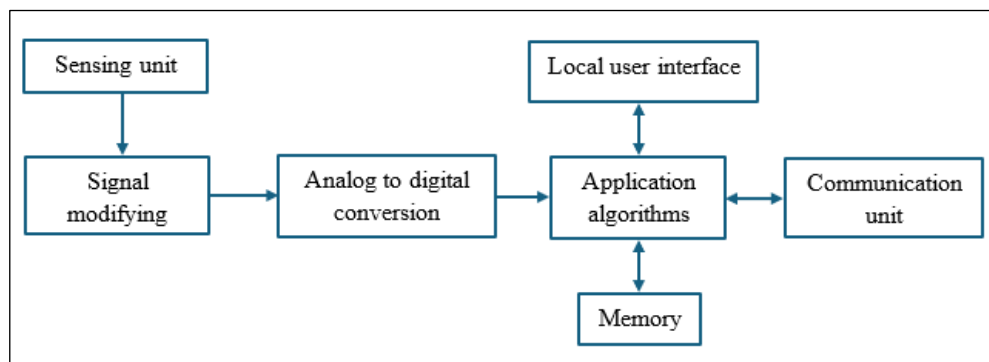


Figure 4: Schematic blocks of smart sensors.

Source: Authors, (2026).

Microprocessor unit (MPU). The MPU is usually considered the main control unit, or “brain”, of a smart sensor. In addition to processing incoming signals, it also controls the internal functions of the sensor. Two of the most important functions of the MPU are signal conditioning and self-diagnosis.

Signal modifying. The raw sensor data is processed by the MPU before being sent directly to the control system. At this stage, filtering, noise reduction, and initial signal correction are performed. The goal is to transmit only useful and reliable data [32].

Self-diagnosis. The MPU also continuously monitors the status of the sensor. Functions such as self-calibration and automatic zeroing are widely used in this process [33]. These capabilities help to detect and automatically correct deviations in sensor performance at an early stage. In traditional sensors, such problems often require manual testing or additional programming.

Another important point to pay attention to in the MPU design is power consumption. Low power consumption ensures long-term uninterrupted operation of the sensor, especially in systems where battery replacement is difficult.

Communication block. This exchanges information between the smart sensor and external devices or a central control system [17]. In addition to measurement results, additional information such as the sensor identification number, operating status, and connection status are also transmitted through this module. In many systems, the communication block allows the central controller to automatically configure the sensor, which greatly simplifies system expansion. Smart sensors usually operate as part of a sensor network. One of the advantages of this approach is that when new sensors are added, there is no need to make significant changes to the existing wiring infrastructure. Communication can be organized in a wired or wireless manner. Fieldbus protocols are mainly used in industrial environments, while BACnet is more widely used in building automation systems [16], [34]. As a result, the combined operation of these components provides smart sensors with more accurate, reliable, and efficient monitoring and control capabilities in various industrial and non-industrial areas.

Types of sensors. Smart sensors can be classified according to various criteria. These criteria include the functionality of the sensor, its energy consumption, and the type of physical phenomenon it measures.

Based on their operational characteristics, smart sensors are usually divided into two main groups: active and passive. Below is an overview of the most common types of smart sensors in industrial environments.

Passive and active sensors. Modern manufacturing systems are built on a number of technological components. These include sensors, actuators, controllers, effectors, and control circuits [35]. Sensors play a particularly important role in these systems, as they contribute to improving product quality by collecting accurate information from the manufacturing process. Sensors are usually electrical, optoelectronic, or electronic devices and are made of sensitive materials. Their main task is to detect the presence of certain objects, conditions, or functions [36]. In many cases, the sensor converts a physical stimulus into an electrical signal. These signals are then processed and used to make decisions about ongoing operations [35], [37]. Recent advances in sensor technology have enabled manufacturers to collect and manage data more effectively than ever before. Sensors can be either active or passive, depending on their operating principles [35], [38]. Active sensors require an external physical stimulus to operate. For example, color recognition sensors require a visible light source to illuminate the surface of an object. Passive sensors do not require any additional stimulus. Infrared sensors are a good example of this, as they detect the thermal radiation naturally emitted by objects such as the human body. A wide variety of sensors have been developed and are successfully applied in industrial process control. Smart factories use a wide range of sensors, from simple temperature and humidity measurements to more complex position and product sensors [39], [40]. These sensors improve production efficiency by supporting processes such as product flow tracking, robot control, milling operations, and environmental monitoring. The most commonly measured parameters in a factory setting are temperature, position, force, pressure, and flow [40].

Temperature sensors. Temperature is one of the key parameters in industrial processes. Because temperature directly affects the physical properties of a material and the quality of the final product. A temperature sensor is a device that collects temperature-related data and converts this data into a form that can be read by other devices [23]. These sensors are used to measure the thermal properties of gases, liquids, and solids. Recent developments in temperature sensor technologies have allowed sensors to operate in both electrically and chemically aggressive environments. This has significantly expanded their application areas. Temperature sensors can be broadly divided into two main groups. The first group is low-temperature sensors that measure temperatures from -100°C to $+400^{\circ}\text{C}$. These sensors are mainly made using phosphors, semiconductor materials, and liquid crystals. The second group is high-temperature sensors designed to operate in the temperature range from 500°C to 2000°C . These sensors are usually based on the principles of blackbody radiation [16], [40], [41].

Thermistors. Thermistors are known as temperature-sensitive resistors, and their electrical resistance changes with temperature. These sensors typically operate effectively over a temperature range of -50°C to 250°C [1], [4], [5], [18], [42], [43]. They are widely used in the automotive industry to measure the temperature of engine intake air and coolant. The main advantages of thermistors are their fast thermal response and minimal errors due to lead wire resistance. However, their temperature range is limited and their resistance to mechanical shock is not considered high.

Resistance thermometers. Resistance thermometers have a stable and predictable relationship between temperature and resistance. This property makes them superior in terms of high accuracy and stability. The measurement range for thin-film sensors is -50°C to 500°C , while for wide-film sensors this range can increase from -200°C to 850°C [44]. These sensors are widely used in HVAC systems, room and duct temperature monitoring, refrigeration, motor overload protection, and automotive applications. Their advantages include high accuracy, strong output signal, and long-term stability. However, their relatively high cost, sensitivity to lead wire resistance, as well as slow thermal response and poor vibration resistance are noted as disadvantages.

Thermocouples. Thermocouples generate a voltage when the temperature changes, which is then converted into a temperature reading. They can measure over a very wide temperature range from approximately -250°C to 3000°C . They are widely used in industrial temperature measurements due to their robust construction and reliability. The main advantages of thermocouples are their wide measuring range, fast thermal response, high temperature capability, and high resistance to shock and vibration. However, the need for compensation conductors when the lead wires are extended is considered one of their main disadvantages.

Pressure sensors. These sensors are basically devices that sense changes in pressure and express these changes in the form of an electrical signal. Here, the level of the output signal directly depends on the applied pressure. This type of electromechanical sensors is widely used to measure the force generated in various environments, and the data obtained is usually transmitted to control or display systems [41], [43], [45]. Pressure sensors are used not only in industrial processes, but also in environmental monitoring. For example, barometric pressure sensors help predict weather conditions by monitoring changes in atmospheric pressure. Vacuum sensors are designed to measure levels below atmospheric pressure. It should be noted that such measurements are often difficult and inaccurate using classical mechanical methods. One type of pressure sensor is the resonant type sensors. These sensors operate on the principle of a vibrating wire. In their structure, there is a magnetic spiral connected to a diaphragm, and vibration is created under the influence of a magnetic field that conducts an electric current. The frequency of the vibration varies with the amount of applied pressure. Resonant pressure sensors are mainly used in industrial measuring instruments and vacuum measurements. Their main advantage is that they can withstand high overpressure and burst pressure. However, the high cost of quartz material and the limited processing capabilities limit the use of these sensors to some extent. Another common type is capacitive pressure sensors. In these sensors, the capacitance changes when pressure is applied to the diaphragm, and this change affects the frequency of the oscillator. Capacitive sensors are particularly advantageous in flow measurement applications. Their high sensitivity allows them to measure both low and high pressure changes. There are cases where they can even measure pressures below 10 mbar and withstand high loads. However, the choice of material, as well as the requirements for assembly and sealing, can limit the application area of these sensors. Piezoelectric pressure sensors, on the other hand, are based on a different working principle. These sensors use piezoelectric materials such as quartz to generate an electric charge proportional to the force when pressure is applied. They are mainly suitable for measuring rapidly changing dynamic pressures. They are widely used in fields such as turbulent flows, explosion processes, engine combustion, and arterial pulse monitoring. The advantages of piezoelectric sensors include fast response time and high dynamic measurement capability. However, these sensors require high impedance circuitry, are sensitive to noise, and are not suitable for static, i.e., constant pressure measurements. Figure 5 shows the effect of temperature on the output signal of a piezoresistive pressure sensor [46].

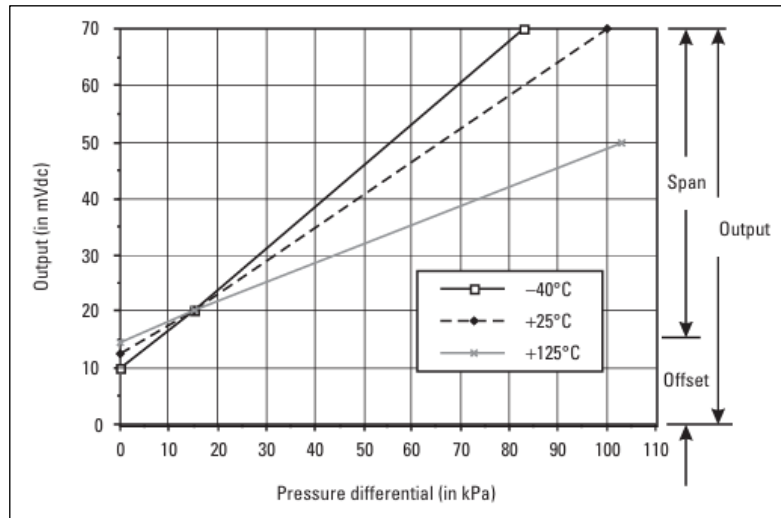


Figure 5: Impact of Temperature on Piezoresistive Pressure Sensor Output.
Source: [46].

The figure shows that the output voltage of a piezoresistive pressure sensor is directly proportional to the applied pressure differential, but the output line and span vary as the temperature changes. For example, the output is higher at -40°C and lower at $+125^{\circ}\text{C}$, indicating the temperature dependence of the sensor and the change in offset/span.

Optical pressure sensors. Optical pressure sensors use interferometry to detect pressure changes in optical fibers. They can be fabricated with small components or MEMS technology. They are commonly found in radiography equipment. They have many advantages: they are not subject to electromagnetic interference, can operate in noisy environments, have high sensitivity, are small, have a long life, and are safe for medical implantation. Their disadvantages are that they are expensive and are affected by physical shocks and environmental influences. The Föppl-von Kármán equations cannot be solved analytically. Therefore, Hallynck and Bienstman used ANSYS to calculate the stress induced by pressure on a 60 m x 60 m, 220 nm thin silicon membrane [47]. Figure 6 shows that the plane stress (σ_{xx}) at the center of the membrane responds nonlinearly to pressure. Simply put, as the pressure increases, the stress is not linear, but rather “flattens” slightly and then increases rapidly.

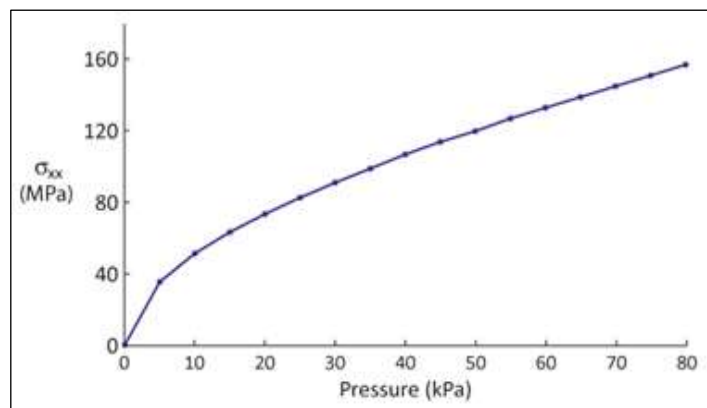


Figure 6: Nonlinear response of the plane stress (σ_{xx}) at the center of the membrane to applied pressure.
Source: [47].

Infrared sensors. An infrared (IR) sensor is an electronic device that detects and monitors the infrared radiation around it. It can identify objects or changes in the environment based on the infrared radiation they emit. Historically, infrared radiation was first known to science in 1800 through experiments conducted by astronomer William Herschel [48]. Herschel observed in his experiments that the temperature rose sharply immediately after the end of red light, thus discovering infrared waves. In fact, this radiation is invisible to the human eye because its wavelength is longer than the range of light we can see. One of the fundamental principles of nature is that any object with a certain temperature necessarily emits infrared energy.

Characteristics of IR spectrum. Infrared sensor technologies mainly cover the range between 0.75 and 1000 micrometers. In terms of location, these waves lie at the intersection of visible light and microwaves in the electromagnetic spectrum. This spectrum is usually divided into the following three specific regions based on wavelength:

1. Near infrared (NIR): The zone starting from approximately $0.75\ \mu\text{m}$ and ending at $3\ \mu\text{m}$.
2. Mid-infrared (MID): This includes wavelengths between $3\ \mu\text{m}$ and $6\ \mu\text{m}$.
3. Far-infrared (FAR): The entire spectrum with wavelengths above $6\ \mu\text{m}$ is included.

Classification of sensor systems. Based on their operating mechanisms, IR sensors can be divided into two main groups.

Active-type sensors. These devices act as both a source of radiation and a collector of reflected light. The process is based on the interaction of a light-recording LED (acting as a transmitter) and a photodiode (receiver).

Passive sensors: This group of devices does not emit any energy themselves, but simply detects infrared signals naturally emitted by external objects. According to the research of Abidin and Ahuja, these systems can distinguish between subjects that are in thermal equilibrium with the environment, that is, those that emit different temperatures [49]. If an unauthorized entry into the area is detected within a certain time frame, the system automatically reacts by activating the signal and as shown in Figure 7, establishes a connection with the numbers previously entered the system. The advantage of this method is that it requires very little computing resources and is widely used for monitoring purposes in both industrial and "smart home" projects.

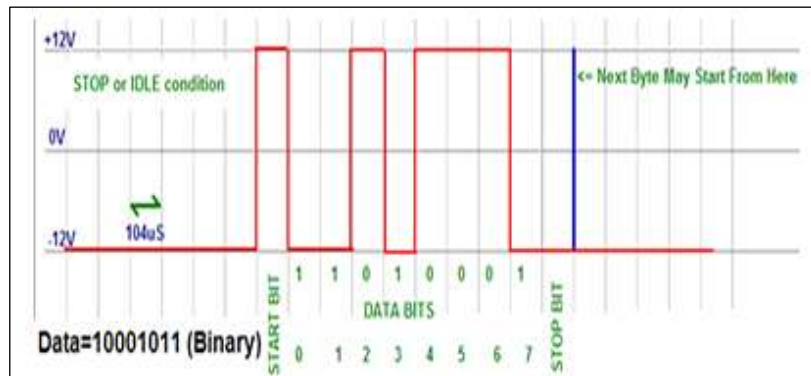


Figure 7: Signal generated by a PIR.
Source: [49].

Active sensor technology. Active sensors absolutely require an external power source to operate. This type of sensor processes any observed physical change and converts it directly into electrical energy or another usable form. Unlike passive types, active sensors do not simply analyze the existing signal but also form their own internal output signals.

Thermocouples. A thermocouple is a type of temperature transducer formed by joining the ends of two dissimilar metals. The basic mechanism here is based on the Seebeck effect: the temperature difference generated at the junction is directly converted into a measurable voltage. Their fast response and resistance to physical impacts have made these sensors indispensable in harsh environments such as industrial furnaces and boilers. The physical and chemical conditions of the environment play a decisive role in the selection of thermocouples when measuring temperature. For example, type E sensors are specifically designed for temperatures up to 1650°F (900°C) in vacuum or slightly oxidizing atmospheres. This type provides the highest EMF output per degree of increase in temperature of the generally accepted thermocouples and shows serious resistance to corrosion at cryogenic temperatures. On the other hand, type J is distinguished by its effectiveness in general-purpose applications where there is no moisture. However, the tendency of the iron wires inside this type to oxidize after 1000°F (540°C) requires protective measures to be taken at its maximum operating temperature limit of 1400°F (760°C). Perhaps the most widely used and universally applicable type in industry is the type K thermocouple. These sensors, which can operate up to 2300°F (1260°C), are corrosion resistant and can withstand a variety of aggressive environments. The N type, which operates at a similar temperature range (1260°C) but is more resistant to oxidation and sulfurous atmospheres than the K type due to its nickel-based composition, is an ideal option for long-term operation. When it comes to monitoring low-temperature and cryogenic processes, the T type sensors provide more stable results. Operating in the range of -330°F to 660°F (-200°C to 350°C), this type can even be used in extreme cold conditions (-269°C), such as the boiling point of helium. Finally, the S and R types, made of noble metals, are used at very high temperatures, such as 2640°F (1450°C). The high sensitivity of these sensors to contamination in reducing environments requires their protection with gas-tight ceramic tubes and additional mechanical layers. A comparative analysis of the general operating temperatures of different types of thermocouples is reflected in Table 2.

Table 2: Thermocouple type and temperature range in Celsius.

Thermocouple type	General application range
E	95°C – 900°C
J	95°C – 760°C
K	95°C – 1260°C
N	95°C – 1260 C
R	870°C – 1450 C
S	980°C – 1450 C
T	-269°C – 350°C

Source: Authors, (2026).

Several different factors can affect the performance of thermocouples manufactured to ASTM (American Society for Testing and Materials) and IEC (International Electrotechnical Commission) standards. Studies by Webster have shown that even very small deviations from the composition of the reference materials can cause significant changes, especially in base metal thermocouples. This effect is most pronounced in the temperature range between 200°C and 600°C [22]. Cold working effects remaining during the manufacturing process can reduce the Seebeck coefficient and cause rapid drift in base metal thermocouples. However, the test methods used to verify compliance with the standards do not always fully reflect real-world operating conditions. Because the number of temperature points selected during the test, the duration of the test, and the source of the samples used directly affect the measurement accuracy. The initial annealing condition is of particular importance in alloy thermocouples.

Although heat conditioning in many cases prevents drift at low temperatures, in some cases it causes unusual behavior compared to standard references. Such cases are mainly observed in K, N, S and R type thermocouples.

Piezoelectric sensors. Since the discovery of piezoelectricity in 1880, piezoelectric materials have been widely used in both scientific research and practical applications. These materials generate an electric charge under mechanical stress or pressure. The reverse process is also possible, that is, a change in the size of the material occurs when an electric field is applied. These properties make piezoelectric materials useful in areas such as sensors, actuators, medical devices and energy harvesting systems. The ability to convert mechanical energy into electrical energy allows them to be used in various fields from electronics to the aerospace industry. Piezoelectric sensors work mainly by generating an electric charge when subjected to mechanical stress or vibration. Piezoceramic materials can be used as a conductive material for the mutual conversion of electrical and mechanical energy. When mechanical vibration is applied, a proportional electric charge is generated at the same frequency. This property is widely used in piezoelectric sensors, especially in high-frequency measurements. Modeling piezoelectric sensors is useful for crack detection and other measurement applications. These models help to better understand the sensor parameters and ultimately allow for their optimization. This knowledge plays an important role in the design of more advanced sensors in the future. Studies by Sedlak and Hefner show that piezoelectric sensors can be described in four different ways. Based on simple measurements, they suggested that a new type of model could be created [8]. Experimental results (Figure 8 (a) and (b)) show that the sensitivity of the sensor does not depend only on the piezoelectric properties and geometry of the material. At the same time, the input signals, impedance (equivalent circuit), and the electrical circuit to which the sensor is connected also affect this sensitivity. At present, a direct mathematical relationship between mechanical vibration and electrical properties has not been fully formulated. However, establishing such a relationship is considered essential for integrating the piezoelectric sensor model into the electrical circuit and for more accurate estimation of the signal-to-noise ratio.

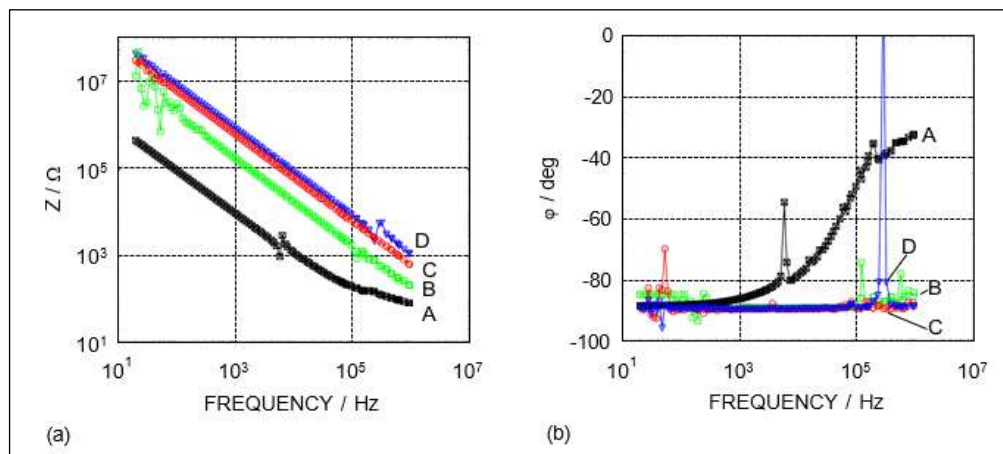


Figure 8: Impedance variation of four sensors with frequency (a) and phase dependency on frequency for four sensors (b). Source: [8].

Capacitive sensors. These sensors are a type of sensor used to make measurements without direct contact. These sensors detect physical or mechanical changes and convert them into electrical quantities. In terms of their working principle, they are similar to a conventional capacitor with a measuring capacity. In practice, capacitance sensors are used to determine displacement, angular displacement, vibration, speed, pressure, as well as some environmental properties. The operating principle of this type of sensor is based on the change in capacitance between two electrodes. When the distance between the electrode's changes, their area changes, or the properties of the medium between them change, the capacitance also changes. In other words, mechanical or physical changes directly manifest themselves as a change in electrical capacitance. A change in any of these parameters causes a change in capacitance. If two of the parameters are kept constant and only one changes, this change becomes an easily measurable capacitance difference. It is this property that allows capacitive sensors to be widely used in measurement systems. A critical analysis of the presented technologies [20], [27], [31] shows that despite the high sensitivity of modern capacitive and piezoelectric sensors, their application in real-life workshop conditions is fraught with the problem of electromagnetic interference. Contrary to optimistic theoretical models, practical studies [32], [42] confirm that "raw" data from sensors without adaptive signal filtering algorithms can lead to false-positive triggering of predictive maintenance systems. To better understand the technological gap between different types of measurement devices, it is essential to conduct a systematic comparative analysis. Table 3 systematizes the main features of smart sensors and highlights their critical drawbacks that are often overlooked in purely theoretical studies.

Table 3: Comparative critical analysis of modern sensor technologies in the context of predictive maintenance systems.

Sensor type	Advantages	Critical disadvantages and risks	PdM readiness level
Vibration (MEMS/IEPE)	The gold standard for rotating equipment.	High sensitivity to background noise. Sophisticated signal filtering is required in noisy environments.	High
Acoustic emission	Detection of microcracks during the beginning stage.	Difficulty in interpreting data. The large volume of raw data overloads network bandwidth.	Average
Optical	Non-contact method, accuracy down to a micron.	Environmental sensitivity. In the presence of dust or steam, the efficiency drops to zero.	Average

Current analysis (MCSA)	It does not require the installation of sensors on the device itself.	Blind spots. Poor detection of mechanical defects in the early stages compared to vibration.	High
Smart sensors (Edge AI)	On-site pre-processing.	Energy paradox: Internal computing drastically reduces the battery life of wireless nodes.	Growing
Gas / Chemical	Early detection of insulation overheating and leaks.	Cross-sensitivity problem. They often give false signals due to changes in humidity or additives.	Low/Medium

Source: Authors, (2026).

The analysis of Table 3 shows that no existing sensor technology is universal. A critical obstacle identified in our review is the lack of integration: most PdM systems are based on isolated metrics. We argue that the future of Maintenance 4.0 lies not in increasing the hardware accuracy of sensors, but in the development of multimodal data fusion algorithms (sensor fusion), where the weaknesses of one sensor type (e.g., vibration sensitivity to noise) are compensated by the strengths of another (e.g., current analysis stability).

IV. PREDICTIVE MAINTENANCE APPROACHES AND PERFORMANCE INDICATORS

IV.1 OVERVIEW OF MAIN PREDICTIVE METHODOLOGIES AND KEY PERFORMANCE INDICATORS

The transition from sensors to analytics requires a clear understanding of the methodological framework. The effectiveness of modern maintenance strategies is determined not only by the quality of sensor data, but also by the selection of an appropriate analytical approach for its interpretation. This section provides a critical overview of the main predictive methodologies and key performance indicators (KPIs) that allow assessing the true contribution of PdM systems to equipment reliability. Yavuz et al. investigated the application of Reliability-Centred Maintenance (RCM) in a tablet chocolate packaging line at ETI Food Industry and Trade Inc., Turkey, with the objective of improving Overall Equipment Effectiveness (OEE) and equipment sustainability [11]. The study highlighted the limitations of conventional time-based maintenance, which was insufficient in preventing functional losses and unplanned breakdowns. A multidisciplinary RCM team was formed, and critical equipment was selected using key performance indicators such as MTBF, MTTR, breakdown frequency, quality losses, and OEE. The packaging machine was systematically analysed through equipment function identification, failure mode and effect analysis, and structured decision-making using RCM information and decision forms. Condition Based Maintenance interventions were initially implemented to restore baseline performance, followed by the formulation of detailed maintenance job steps, parameter settings, and operator instructions for different product specifications. The implementation led to improved equipment availability, reduced quality related losses, and a marked increase in OEE within a six-month evaluation period. The authors concluded that RCM significantly strengthened maintenance effectiveness, supported autonomous maintenance and TPM principles, and promoted sustainable and reliable operations in the food manufacturing sector. Castañeda et al. investigated the improvement of machinery availability in a Peruvian food manufacturing company through the integrated application of Total Productive Maintenance (TPM), Single Minute Exchange of Die (SMED), and Reliability-Centred Maintenance (RCM). The study focused on the confectionery production line, where machinery availability was limited to 79.06 percent, significantly below the world class benchmark of 90 percent, resulting in economic losses and reduced operational efficiency [12]. A structured improvement model combining planned maintenance with RCM, setup time reduction through SMED, and autonomous maintenance under TPM was implemented and validated through a pilot study.

Key performance indicators including MTBF, MTTR, OEE, process time, and scheduled maintenance index were monitored. The results demonstrated a 13.01 percent increase in OEE, an improvement in availability from 79.06 percent to 89.37 percent, a 41 percent reduction in setup time, and a 65 percent reduction in preventive maintenance duration [12]. Additionally, MTBF and MTTR showed notable improvements, indicating enhanced equipment reliability and faster recovery from failures. The authors concluded that the synergistic integration of TPM, SMED, and RCM provides a practical and sustainable framework for improving machinery availability, productivity, and cost efficiency in the food industry, with strong potential for long term industrial adoption. Álvarez García et al. compared preventive and predictive maintenance strategies for a multi-stage thermoforming machine used in food packaging, focusing on reliability, efficiency, and availability [13]. The study evaluated four strategies over one year of continuous industrial operation: Preventive Programming Maintenance (PPM), Improved Preventive Programming Maintenance (IPPM), Algorithm Life Optimisation Programming (ALOP), and Digital Behaviour Twin (DBT). While PPM and IPPM achieved high availability through scheduled component replacement and reduced MTTR, they failed to detect unexpected failures. In contrast, ALOP and DBT, based on sensor data and algorithmic analysis, successfully identified early failure signatures before catastrophic breakdowns occurred. The DBT approach, which evaluates sensor behaviour relative to encoder-based machine position patterns, demonstrated superior accuracy and fewer false alarms compared with ALOP. Although predictive strategies reduced calculated efficiency and availability due to earlier failure detection, they significantly improved operational reliability by preventing unplanned stoppages. The authors concluded that DBT is particularly suitable for multi-stage machines due to its precise behavioural pattern recognition, and that hybrid integration of preventive and predictive strategies represents the most robust framework for maintenance management in complex multi-stage industrial manufacturing systems. Shaurya investigated the performance of solid lubricant bearings in starch confectionery washdown environments using a starch molding machine for jelly and gummy production, where conventional lubricated bearings frequently failed due to starch dust ingress, hot water cleaning, humidity, and lubricant washout. A data driven comparison was conducted by replacing standard bearings with solid lubricant bearings in critical zones such as feeders, stackers, depositors, and buck systems, and monitoring failure frequency, maintenance needs, and operating life. The results showed a marked reduction in bearing replacement frequency, lower maintenance intervention, and approximately 25 percent annual cost savings, while visual inspections confirmed that conventional bearings accumulated starch water paste near seals and suffered lubricant leakage, leading to premature damage [14].

In contrast, solid lubricant bearings-maintained lubrication integrity during repeated washdown cycles, especially when combined with stainless steel housings and proper sealing, ensuring corrosion resistance and food safety compliance. The study concluded that solid lubricant bearings significantly improve reliability, hygiene, and machine availability in starch confectionery processing, making them a highly effective solution for increasing productivity by reducing downtime.

IV.2 DISCUSSION OF THE ROLE OF SENSORS, IOT AND AI IN PREDICTIVE MAINTENANCE (PDM)

The Internet of Things (IoT) is increasingly playing a key role in predictive maintenance systems. The main reason for this is that IoT technologies can collect data from machines and equipment in real time and transmit this data over long distances. The operating status, overall performance and environmental conditions of the equipment can be continuously monitored through sensors installed in the production environment. IoT-based devices collect data on temperature, vibration, pressure and similar parameters and transmit them to central control systems or cloud platforms. This approach allows maintenance teams to monitor equipment without having to be directly in the field. As a result, problems are detected at an earlier stage, unexpected downtime is reduced and the equipment's service life is extended. Some of the key benefits of IoT in PdM systems are:

- Real-time data acquisition for continuous monitoring of equipment
- Remote monitoring of machines and reduction of on-site intervention
- Ability to act before failures occur
- Making more informed decisions based on collected data.

By [15] proposed a novel blockchain and IoT-based food safety architecture specifically designed for the confectionery supply chain to address critical issues related to transparency, traceability, trust, and real-time monitoring in Industry 4.0 environments. Using a mixed qualitative methodology that included surveys of 78 managers and in-depth interviews within a confectionery manufacturing business organization, the study identified key gaps such as raw material traceability, fragmented information systems, error-prone reconciliation, and limited visibility of product status during storage and transportation. The authors propose a multi-layer blockchain architecture based on Ethereum-based distributed ledger technology. This architecture supports tokenized ownership transfer and integrates IoT sensors, information management mechanisms, smart contracts, and application-presentation layers into a single system. The IoT sensors used in the system continuously monitor temperature, humidity, vibration, and storage conditions. The collected data is stored on the blockchain, allowing for an immutable yet verifiable record of product origin, quality certificates, logistics processes, and regulatory compliance. This approach also facilitates secure sharing of data between different parties. The proposed system has significant potential in terms of increasing food safety and reducing waste. At the same time, it contributes to improving regulatory compliance and supporting sustainability by tracking recycling processes with reverse logistics. The study found that blockchain IoT integration provides a reliable digital foundation for confectionery supply chains, enabling real-time visibility, increased trust among stakeholders, and more sustainable, transparent, and efficient food safety management in line with Industry 4.0 goals.

In the study presented in [50], an IoT-based predictive maintenance system was implemented for hospital mechanical equipment. The study focuses on autoclave equipment used in King Faisal Hospital. The system acquired real-time data through a custom-built data collector and used Long Short-Term Memory (LSTM) models to provide predictions with 90% and 96% accuracy for two key components, respectively. The main goal of this approach is to reduce downtime while increasing equipment reliability and availability. Although the study presents successful IoT-based PdM architecture, it does not address the issues of prioritization and scheduling of maintenance activities. However, the proposed structure can be adapted for other industrial equipment with similar operating parameters.

The role of sensors in predictive maintenance. Sensors are the basis of predictive maintenance systems. They continuously measure important parameters such as temperature, humidity, vibration and pressure in machinery and infrastructure elements. Thanks to these measurements, processes that can lead to wear, deterioration and failure can be observed at an early stage. Sensors integrated into equipment provide timely information about conditions such as overheating, excessive vibration or unusual pressure changes. This information, in turn, serves as the main input for predictive models. Sensors used in industrial monitoring differ according to the functions they perform. The most common are:

- Vibration sensors monitor signs of mechanical imbalance or failure
- Temperature sensors detect thermal anomalies in components
- Pressure sensors identify irregularities in hydraulic and pneumatic systems
- Proximity sensors monitor the position and alignment of moving parts

Several studies have focused specifically on sensors used in machine vibration monitoring. For example, [6] examines in detail the importance of vibration analysis in industrial equipment and the sensor technologies used for this purpose. Accelerometers and strain gauges are among the most widely used sensors in vibration analysis. IEPE-type accelerometers are considered effective in measuring dynamic vibrations with high accuracy in real time. Strain gauges detect small changes in resistance due to mechanical deformation and are useful in structural analysis. Recently, the development of eddy current sensors for non-intrusive vibration measurements has attracted attention. These sensors can measure vibrations occurring on metal surfaces without direct contact. This feature is particularly advantageous in industrial applications where surface damage is unacceptable. These sensors are considered promising in terms of both sensitivity and ease of application compared to traditional measurement methods. However, environmental noise and limited physical access to equipment are the main factors that make it difficult to apply vibration analysis methods in food machinery. To overcome these limitations, the application of new approaches that increase the accuracy of vibration measurements may be appropriate [6]. Another study [7] investigated the use of infrared imaging technology as a non-destructive monitoring method in the food processing industry. This approach allows for the detection of problems such as friction, overheating and energy loss in machinery without direct contact.

Infrared thermography allows for real-time monitoring of the thermal behavior of components, which is of particular importance in terms of food safety and production quality. The application of this technology allows maintenance teams to identify problems before they become serious failures and increases overall operational efficiency. Infrared imaging analysis in food processing can be affected by ambient temperature, humidity, the need for expensive specialized hardware and software, time-consuming calibration and recalibration by qualified technicians, and limited effectiveness in detecting certain contaminants, all of which can limit its general application [7].

Artificial Intelligence (AI) in PdM. AI is increasingly being used in PdM. AI helps to predict equipment failures by analyzing data from IoT devices and sensors. This makes predictive maintenance more efficient. Machine learning (ML) algorithms play a key role at this situation. ML models find patterns in historical data and sensor readings, create models that predict when maintenance will be needed in the future. These models can predict, for example, when a component will fail, allowing companies to intervene in a timely manner. A study [51] shows how AI can be applied to PdM. It used a synthetic dataset for demonstration purposes - machine sensor measurements and 10,000 failure events. The machine's condition is classified as either broken or operational using artificial neural networks. The study shows that the biggest challenge is obtaining quality data. That's why synthetic data is used. Collecting real data is often expensive and difficult. Supervised learning models, especially Support Vector Machine (SVM), Random Forest, and Artificial Neural Networks (ANN), have shown high accuracy in fault classification. The accuracy of SVM models on various industrial datasets has been in the range of 85–94% [9], [52]. ANN models have shown higher results in some cases [53]. Deep learning-based models, especially LSTM and DNN architectures, have shown superior performance in RUL prediction. On the NASA C-MAPSS dataset, LSTM models have provided more accurate predictions with lower error rates [10]. CNN-LSTM hybrid models, on the other hand, have provided more stable results in complex systems by processing both spatial and temporal features together [2], [19]. Overall, AI-based PdM systems offer significant benefits in terms of reducing downtime, optimizing maintenance costs, and increasing equipment uptime [3], [9]. However, data quality, computational costs, and model interpretability remain major limitations [54], [55]. This remains a challenge for enterprises that lack new and long-term failure data.

V. CONCLUSIONS

In summary, smart sensor systems increase situational awareness in industrial areas, increase operational efficiency, and ensure reliability in various applications. Equipped with advanced capabilities such as signal conditioning, self-calibration, and network integration, these systems offer significant advantages over traditional sensors. These systems, which convert physical quantities into electrical signals through transducers, provide monitoring of many environmental and operational parameters. The application potential of passive and active sensors has expanded from industrial automation to environmental monitoring. By using artificial intelligence technologies, industries can achieve more accurate monitoring, data-driven decision-making, and optimized operational performance. Despite the latest innovations, several research gaps still exist. For example, the full application of dynamic wear analysis in real-time of confectionery equipment is still under development. Energy efficiency and optimization of kinematic parameters are not yet supported by sufficient practical models. The application of multi-criteria optimization models to confectionery machinery is limited, and models that are economically accessible for SMEs are almost non-existent. Furthermore, specific application models for ML algorithms to avoid unexpected failures have not yet been sufficiently developed, especially for limited data conditions. In the future, addressing these research gaps will greatly contribute to making industries more efficient, reliable and sustainable.

VI. AUTHOR'S CONTRIBUTION

Conceptualization: Hamid Abdullayev, Elnur Huseynzade.

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Investigation: Hamid Abdullayev.

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Supervision: Elnur Huseynzade.

Approval of the final text: Hamid Abdullayev, Elnur Huseynzade, Harsh Sable.

VII. DECLARATIONS

Declaration of generative AI and AI-assisted technologies in the writing process: During the preparation of this work, the authors used ChatGPT in some sections to improve readability and language, and to prepare the bibliography in IEEE format. After using this tool/service, the authors reviewed and edited the content carefully and take full responsibility for the content of the publication.

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