International Journal of Emerging Trends in Engineering and Technology
ISSN: 3107-8699 | Volume 2 Issue 3, 33-47, July-September 2026
DOI: https://doi.org/10.64137/31078699/IJETET-V2I3P104

Received: 23/06/2026 Revised: 20/07/2026 Accepted: 28/07/2026 Published: 05/08/2026

Original Article

A Comprehensive Review of Recent Advances in Smart Sensors and Transducers for Industrial Measurement and Automation

DR PANKAJ MOHINDRU
Department of Electronics & Communication Engineering, Punjabi University (A State Government University), Patiala, Punjab, India.

ABSTRACT: *The use of smart sensors and transducers has changed from a niche tool to one that is now considered a basic technology for industrial measurement and Automation, allowing accurate acquisition of information, intelligent monitoring, and autonomous control of industrial processes. This review covers the latest developments in smart sensing technologies and their role in the fields of Industry 4.0, Industrial Internet of Things (IIoT), and Smart Manufacturing (SM4.0). The paper covers the development of smart sensors, transducers, industrial measurement systems, wireless sensor networks, artificial intelligence, machine learning, edge computing, and the integration of digital twins for enhancing the performance of industry. Advancements in microelectromechanical systems (MEMS), nanoelectromechanical systems (NEMS) and other advanced fabrication technologies, fibre-optic sensing technology, wireless communication and embedded intelligence have enhanced the accuracy, reliability and performance of sensing. It also examines the applications of intelligent sensing in predictive maintenance, robotics, quality inspection, data mining and analysis tools for process monitoring, energy management, control information acquisition and autonomous manufacturing. Beyond this are critical issues of interoperability, cybersecurity, energy efficiency, communication reliability and standardization. Lastly, future research directions focusing on Explainable Artificial Intelligence, Edge Intelligence, Advanced Communication Technologies, and Sustainable Sensing Architecture are pointed out. Smart sensors and transducers will be crucial to advanced digital manufacturing and sustainable industrial transformation that give rise to a larger network of resilient, connected, and intelligent industrial automation systems.*

KEYWORDS: *Smart Sensors, Transducers, Industrial Measurement, Industrial Automation, Intelligent Sensing, Sensor Technologies, Internet of Things (IoT), Industry 4.0, Wireless Sensor Networks, Real-Time Monitoring, Sensor Fusion, Predictive Maintenance, Industrial Control Systems, Embedded Sensing, Edge Computing.*

1. INTRODUCTION

The intelligent manufacturing that has been developed by the industry has revolutionized industrial manufacturing with more reliance on data-driven monitoring, precision control and autonomous decision-making (Rakholia et al., 2024). In modern manufacturing, technologies that have been recently popularised allow for efficient performance of complex industrial processes, allowing for highly accurate and real-time information in order to control highly complicated industrial operations (Alginahi et al., 2025). Industrial Internet of Things (IIoT) will now finally envelop the previous cyber - physical systems, with the help of continuously monitoring processes by using machines under Industrial Internet Of things (IIOT), where the basis for all kinds of sensors is. Xu et al., 2018. Unlike conventional measurement tools, modern measuring solutions are able to self-diagnose, constitute digital communication, and adjust adaptively under the flexible production environment to optimize the production process, reduce production cost, and guarantee product quality (Hu et al., 2024).

With the development of technologies like micro-electro-mechanical system (MEMS), nano-electro-mechanical system (NEMS), flexible electronics, optical sensing, semiconductors, and advanced functional materials (Torkashvand et al., 2024), the capabilities of the smart sensors and transducers have enhanced greatly. As a consequence, these advances have led to the development of new, original, accessible, miniature, adaptable sensors that expand effectiveness and incorporate incredibly delicate components directly proportional to actual assessing strategies: mechanical (Tsai et al., 2025), thermal, chemical, optical, acoustic and electrical parameters. Simultaneously, the advancement of wireless communication technologies (such as 5G, Wi-Fi, ZigBee, Bluetooth Low Energy, LoRaWAN) has allowed us to achieve seamless connectivity between any provided sensing devices, industrial controllers, cloud platforms and distributed automation systems Daousis et al., 2024. This enables industrial companies to collect, transmit and process measurement data in real-time, which allows for quicker actions on operations and increased reliability of the system (Noor-A-Rahim et al., 2022).

Utilization of industrial sensing has transformed with the help of Artificial Intelligence (AI), Machine Learning (ML) and Edge Computing, where analysis is being performed at the sensor itself, enabling intelligent data analysis (Ficili et al., 2025). Decentralized learning using acquisition devices (Zhang et al., 2024) is another major type of intelligent sensing and measurement, enabling local signal processing, anomaly detection for predictive maintenance, adaptive calibration and fault diagnosis without relying on a central data-efficient event-driven computing system. Sensor fusion, digital twins, robotics and industrial analytics (Al Zami et al., 2025) enable multi-industry applications for these technologies ranging from manufacturing to health care, transportation to energy, agriculture to environmental monitoring; smart infrastructure. Artificial Intelligence Sensors integrated into an ecosystem can significantly improve the flexibility of an industrial system, optimize the use of its resources, ensure safety, or increase resilience (Dihan et al., 2024).

While these remarkable advancements exist, there are still a number of technical and operational challenges that continue to affect how smart sensing technologies enter industrial Automation. Different devices, cybersecurity issues and communication delays for mobile applications are still some of the top research challenges (Matta et al., 2026 in Shi and Qiu). To overcome these challenges, it is essential to cross disciplinary boundaries and push innovations in electronics and embedded systems, communication networks, artificial intelligence (AI), industrial engineering, et al. (Xue et al., 2026). Therefore, this review aims to cover some recent developments in smart sensors (SS) and smart transducers (ST) with respect to new technologies, future applications in industry, challenges involved in going from concept to implementation, and directions for future research.

2. SMART FACTORY

While Automation is playing a major role in the production of today's factories, innovative manufacturers are taking this one step further by incorporating the Internet of Things (IoT) and artificial intelligence (AI) into their manufacturing processes. In recent years, cyber-physical systems have grown continuously more complex, and physical machines and business processes have increasingly been integrated with automation technologies, allowing for more complex optimization decisions to be made that were previously made by human beings (Ning et al., 2011; Xu et al., 2016). The integration has enabled manufacturers to link shop floor decisions and operational insights with the supply chain activities and hence the introduction of the smart factory concept. The First Industrial Revolution was the introduction of mechanical manufacturing equipment, and the Second Industrial Revolution (Shrouf et al., 2014) was the era of mass production. The Third Industrial Revolution saw ubiquitous use of electronics and information technology to improve Automation and process control (Wilkesmann & Wilkesmann, 2018). The use of IoT in the manufacturing sector has also changed traditional centralized factory management systems to decentralized and interconnected production systems (Wilkesmann & Wilkesmann, 2018; Shrouf et al., 2014; Kaur & Kaur, 2017). These developments have made it possible for machines and manufacturing systems to be able to self-optimize and autonomously reconfigure to adjust to the changing production orders and operating conditions (Dalenogare et al., 2018; Manavalan and Jayakrishna, 2019). The technology that underlies smart factories is the acquisition of data: the use of intelligent sensors, motors, and robotic systems in production and assembly lines to enable real-time monitoring, Automation, and intelligent decision-making (Benitez et al., 2020).

2.1. SMART FACTORY VS. TRADITIONAL FACTORY

The manufacturing process must have skills that help to accommodate sudden shifts in customer preferences and demand, including the ability to adjust the product type and production capacity to accommodate multiple varieties of products (Choy et al., 2020). To cope with such challenges, manufacturing should be sufficiently functional and scalable and should be able to connect with customers and suppliers. However, traditional factories do not have the ability to monitor and control automated and complex manufacturing tasks to produce custom-made products efficiently (Farhangi, 2017). Traditional factories are characterized by the absence of integration between the production system, product life cycle, and value chain, as well as the presence of stand-alone and segregated applications. As a result, the outdated configuration is characterized by inadequate system reuse and integration between actual and virtual systems. The general concept of a smart factory is depicted in Figure 1.

FIGURE 1 Concept of a Smart Factory

The smart factory is the next step beyond traditional Automation and represents the continuous flow of data in the form of highly connected operations and production systems that are able to learn and adapt to fluctuating requirements (Farhangi, 2017; Gattullo et al., 2019; Punithavathi et al., 2019). These factories can integrate information from physical, operational, and human resources to aid manufacturing, maintenance, inventory management, digitization of operations, etc., in manufacturing systems (Burke et al., 2014). The main aim of smart factories is to use intelligent production systems and suitable engineering methods for the successful and interconnected implementation of production facilities (Choy et al., 2020; Kimani et al., 2019). It is an engineering system based on interconnections, collaboration, and execution. The connectivity of devices in smart factories enabled the exchange of information, recognition and evaluation of situations, as well as the integration of the physical world with the digital world, which makes smart factories adaptive (Dalenogare et al., 2018; Frank et al., 2019). That is, the smart factory combines physical and cyber technologies, and improves the accuracy of the technologies involved, thereby improving the performance, quality, controllability, manageability, and transparency of manufacturing processes. The manufacturer can adjust the production specifications and other settings of the machines at the last minute in such a smart factory environment to meet the customer's needs. Unlike traditional factories, this ability is not present (Ivanov et al., 2016) (Table 1). The essence of a smart factory is the ability to adapt and change in response to the organization's increasing requirements (Ivanov et al., 2016; Agrifoglio et al., 2017). These needs can be segmented into the needs of the changing demands of customers, new markets, new product and service development, improved production methods in operations, and application of advanced technologies in maintenance processes (Shrouf et al., 2014; Lightfoot et al., 2013; Tanyingyong et al., 2016). The capacity to adapt and learn from real-time data makes smart factories receptive and predictive in avoiding other potential manufacturing process failures, such as downtime (Wilkesmann & Wilkesmann, 2018; Burke et al., 2014).

TABLE 1 Key Differences between the Traditional Manufacturing Factory and Smart Factory

Traditional Factory	Smart Factory
The absence of integration between systems and technologies has resulted in the manual separation of processes and activities.	New technologies, tools, and systems have been seamlessly integrated to digitize and integrate processes and operations.
Legacy systems are characterized by frequent machine breakdowns and high maintenance costs.	Intelligent systems that optimize machine utilization and reduce maintenance expenses through predictive maintenance.
Process-driven decision-making is characterized by a lack of information for decision-making due to the fact that data is restricted to specific systems or devices.	Comprehensive information accessibility and expedited data-driven decision-making are facilitated by the availability of real-time data from any location.
Limited use of advanced technologies.	Extensive use of Internet of Things (IoT), sensors, mobile applications, and Radio Frequency Identification (RFID).
Limited visibility into operational performance and productivity.	Enhanced transparency and real-time visibility of operations, production performance, and productivity metrics.
Limited innovation in product design and manufacturing processes.	Development of smart and intelligent products supported by advanced digital technologies.
Inaccurate asset tracking and inefficient resource utilization.	Accurate asset tracking through IoT and RFID technologies, leading to optimized resource utilization.
Poor interoperability between machines and systems.	High interoperability enabling seamless communication among machines, devices, and enterprise systems.
Production lines require manual reconfiguration and system shutdown when changing product types.	Production lines automatically reconfigure resources and production routes online without interrupting operations when switching between different product types.

The Smart factory has four intelligent features:

- Sensors: These are sensors that possess the capacity to self-organize, learn, and store ambient data to analyze skills and behaviour. Consequently, sensors are capable of making decisions that allow them to adapt to environmental changes.
- Interoperability: The ability of multiple devices to communicate and adapt to the production system's configuration protocol is enhanced when they are connected.
- Integration: Smart factories accomplish a high degree of process integration by employing robots and artificial intelligence (AI). AI may be implemented in factories for the purpose of analysis and decision-making, in addition to integrating human intelligence.
- One of the advanced technologies of smart factories is virtual reality (VR) methods, which are a component of human-machine integration. Using computers, signal processing, animation, intelligent reasoning, prediction and simulation, and multimedia technologies, this method simulates industrial processes.

3. CLASSIFICATION OF SMART SENSORS

Smart sensors are not one of the latest technologies but have been making headlines for their potential importance and the variety of application areas. As a result of computing and the Internet of Things (IoT) in industrial processes, ordinary sensors have evolved into smart sensors, able to conduct complex calculations based on the data that they collect (Bibby & Dehe, 2018; Landaluce et al., 2020). In addition to their greater capabilities, smart sensors are also very tiny and flexible, making the transformation of large machines to smart systems possible. Smart sensors have been transformed into smart devices that have detection and self-awareness capability owing to the existence of signal conditioning, embedded algorithms, and digital interfaces (Choy et al., 2020; Kim et al., 2019). The aim of these sensors is to be used as components of the IoT system, transforming information that is present in real time into digital data that can be passed to a gateway (Herrojo et al., 2019; Dahlin, 2012). The capabilities allow smart sensors to forecast and monitor real-time conditions and then take corrective actions immediately. The main functions of intelligent sensors (Mulloni & Donelli, 2020) include a variety of complex multi-layered operations: raw data collection, sensitivity adjustment, filtering, motion detection, data analysis, and communication. For example, one of the most important applications of smart sensors is the wireless sensor network (WSN) in which each sensor node communicates with one or more sensor nodes and/or sensor hubs to form an effective communication network. In addition, data from many sensors may be fused to identify a particular event, such as mechanical failure, predicted from temperature and pressure sensor data. The building blocks of a typical smart sensor are shown in Figure 2, while the key features of smart sensors are summarized in Figure 3 (from Le et al., 2019 and Kim et al., 2019).

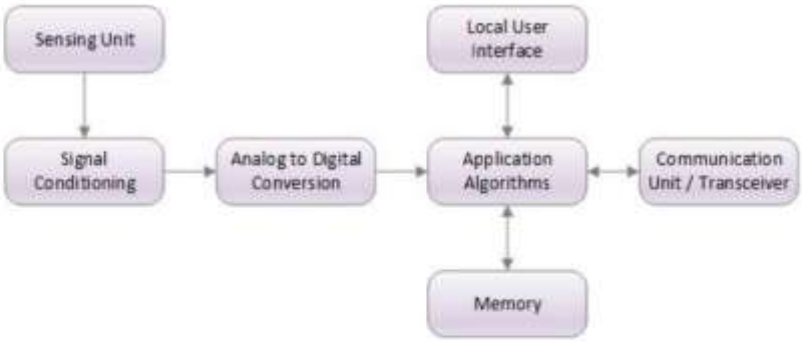

FIGURE 2 Smart Sensor Building Blocks

FIGURE 3 Features of a Smart Sensor

3.1. CALIBRATION CAPABILITY

The capability of a sensor to identify the normal operating condition is called calibration capability (Jeon et al., 2020). Self-calibration is easy in many applications, and various methods of self-calibration are used with various types of sensors.

- Sensors that are electrically driven can make a calibration using a known reference voltage.
- Also, load cells that are part of a weighing system can automatically compensate for the absence of an external load (Gattullo et al., 2019).
- Other sensors use look-up tables for calibration; however, these sensors need a significant amount of memory to store many correction points that were generated during calibration. On the other hand, interpolation methods are usually preferred since they require only a small correction matrix with calibration accuracy, and it is enough to include a few numbers to cover a large range of data (Tanyingyong et al., 2016).

3.1.1. SELF-DIAGNOSIS OF FAULTS

Smart sensors self-diagnose by continually self-monitoring their internal signals for evidence of possible faults. For some sensing systems, it can be difficult to differentiate between normal measurement variation and actual sensor error (Kim et al., 2019). This problem, however, can be overcome by storing multiple measured values around a pre-defined operating point and determining the minimum and maximum values of the measured parameter to detect abnormal behaviours (Zuo et al., 2018). Moreover, uncertainty analysis methods are used to analyze the effect of sensor faults on the measurement accuracy. The methods allow the sensor to operate reliably even after a fault has been detected, which helps to increase the system's reliability, fault tolerance, and continuous monitoring capabilities.

3.2. NUCLEAR SENSORS

Nuclear sensors are found relatively rarely given their high cost and the strict safety regulations for their deployment and operation (Bibby & Dehe, 2018; Li et al., 2016). However, with recent advances in technology, small-scale radiation sources have been developed, and the application of nuclear sensors is now safe and practical in certain industrial and medical uses (Bibby & Dehe, 2018). The characteristics, applications, pros and cons of nuclear sensors are summarized in Table 2.

TABLE 2 Key Features of Nuclear, Micro, and Nano Sensors

Sensor Type	Characteristics	Material	Uses	Advantages	Disadvantages	Source
Nuclear Sensor	Operates on the principles of optical sensors, where a medium facilitates the transmission of radiation between a source and a detector. The magnitude of transmitted radiation is attenuated according to the measured variable.	Cesium-137 as a gamma-ray source; sodium iodide detector used as a gamma-ray detector.	Mass flow measurement, medical scanning applications.	Zero carbon emissions; supports energy independence.	Very expensive; susceptible to contamination from background radiation.	(Li et al., 2016; Shkel, 2001)
Micro-Sensors	Mechanical sensing elements integrated with microelectronics. Typical sensor dimensions range from 0.01 mm (10^{-5} m) to 5 mm.	Silicon semiconductor materials; fabricated using metals, plastics, polymers, gases, and ceramics deposited on a silicon substrate.	Widely used in the automotive industry and medical equipment, including blood pressure measurement.	Smaller size, improved performance, higher reliability, and lower production costs.	Low capacitance; output signals are susceptible to noise contamination and have very low amplitude.	(Li et al., 2016; Shkel, 2001)
Nanosensors	Extremely small sensors with dimensions ranging from 1 to 1000 nm, developed using nanotechnology.	Thin layers of metal films or semiconductors; fabricated using advanced MEMS techniques, optical lithography, and electron-beam lithography.	Used as accelerometers, biological sensors, and chemical sensors for airborne applications.	Lower production costs, reduced power consumption, and ultra-small size.	Difficult to handle; affected by short-term noise issues.	(Kim et al., 2019; Li et al., 2016)

3.3. MICRO-SENSORS (MEMS SENSORS)

The microelectromechanical system (MEMS) devices are composed of micro-machined structures that are two- and three-dimensional (Li et al., 2016; Shkel, 2001). Consequently, micro-sensors are constructed. These sensors are classified as miniature transducers due to their capacity to produce an electrical signal from mechanical input from the energy source. Micro-sensors are widely used by businesses and detect temperature, pressure, force, motion, sound, magnetic field, optical, biological and chemical properties (Bibby et al., 2018; Shkel, 2001). The main characteristics of these sensors are clarified in Table 2.

3.4. NANOSENSORS (NEMS)

Nanosensors, which are founded on nanotechnology, are the most recent advancement in sensing technology (Kim et al., 2019; Shkel, 2001). These are components of nanoelectromechanical systems (NEMS) and nano-actuators. These sensors are summarised in Table 2.

4. SMART TRANSDUCER TECHNOLOGIES

In the current manufacturing automation environment, this hardware has assumed great significance in its appearance and emergence as smart transducer technologies that combine sensing with signal conditioning, embedded processing, communications and self-diagnostic skills on one intelligent device. A smart transducer does not merely change a quantity into an electrical signal, as in the case of traditional transducers; rather, it has computational intelligence cognitive element to become self-calibrating, self-processing and self-compensating with capability for real-time communication localized within an industrial control system. Modern functionality assists precision measurement, reliability to operate and contributes to predictive maintenance operations in complex manufacturing procedures (Kirianaki et al., 2002). Smart transducers consisting of a microcontroller and digital communication interfaces (Belgacem & Chihi, 2025) perform autonomously and can communicate with programmable logic controllers(PLCs), supervisory control and data acquisition(SCADA) systems, distributed control systems (DCSs), cloud systems and landscaping in an Industrial Internet of Things(IIoT).

Smart transducer performance has been vastly enhanced by the advancement of electronics, research on micro-, Nano and Fiber-Optic devices & sensors [1], flexible Devices & nanomaterials (Uvarajan 2024). Micro-Electro-Mechanical Systems based transducers have compact size, low power consumption, fast response with high sensitivity and their application to the measurement of pressure and acceleration; vibration/inertial measurements. Fibre-optic transducers, like piezoelectric ones, are also immune to electromagnetic noise and thus find their use in many dangerous industrial applications; however, the versatile application of piezoelectric sensors for vibration monitoring or ultrasonic inspection and structural health assessment (Sivasuriyan et al., 2024) is worth mentioning. The introduction of new developments in graphene and carbon nanotubes, metal oxides and polymer nanocomposites has enhanced the sensitivity, resilience and long-term stability of the transducers and facilitated the miniaturization and flexible fabrication of devices.

However, today's smart transducer advances also include AI, edge intelligence, wireless capabilities, and decreased energy use, enabling intelligent industrial monitoring. With embedded machine learning algorithms, the sensing node can detect anomalies, perform auto-calibration and execute predictive maintenance and fault diagnosis, which reduces communication latency as well as dependence on cloud resources (Morchid et al., 2025). Wireless communication technologies like Bluetooth low energy (BLE), ZigBee, Wi-Fi, LoRaWAN or 5G can reliably connect various industrial distributed systems. Additionally, the use of innovative power management techniques, including energy harvesting and low-power electronics, extends battery life in sensing applications. As per the study examples mentioned above, with such technological advancement, smart transducers can be used in several areas, such as manufacturing, robotics, healthcare, transportation, energy management, environmental monitoring, and smart infrastructure, depending on the applications that require continuous and reliable measurement to carry out efficient Automation (Pathak, 2019).

TABLE 3 Classification of Smart Transducer Technologies and Their Industrial Applications

Smart Transducer Technology	Operating Principle	Major Advantages	Typical Industrial Applications
Resistive Transducer	Measures changes in electrical resistance caused by physical variables	Simple design, high accuracy, low cost	Temperature measurement, strain gauges, pressure sensing
Capacitive Transducer	Detects variations in capacitance due to displacement or dielectric changes	High sensitivity, low power consumption, excellent resolution	Position sensing, level measurement, humidity detection
Inductive Transducer	Converts displacement through electromagnetic induction	High reliability, robust operation, non-contact measurement	Position control, displacement monitoring, industrial Automation
Piezoelectric Transducer	Generates electrical charge under applied mechanical stress	Fast response, high sensitivity, wide frequency range	Vibration monitoring, ultrasonic testing, structural health monitoring
Optical/Fiber-Optic Transducer	Uses variations in light intensity, phase, or wavelength	Immune to electromagnetic interference, long-distance sensing	Oil and gas, aerospace, power plants, hazardous environments
MEMS-Based Transducer	Employs microfabricated mechanical structures integrated with electronics	Miniaturized size, high precision, low power consumption	Automotive systems, robotics, smartphones, industrial monitoring
NEMS-Based	Utilizes nanoscale mechanical	Extremely high sensitivity,	Nanotechnology, biomedical

Transducer	structures for ultra-sensitive measurements	rapid response	diagnostics, advanced manufacturing
Electrochemical Transducer	Converts chemical reactions into measurable electrical signals	High selectivity, real-time chemical detection	Gas sensing, pollution monitoring, chemical processing
Magnetic Transducer	Measures magnetic field variations using Hall-effect or magnetoresistive principles	Non-contact operation, durable performance	Motor control, speed sensing, industrial robotics
Ultrasonic Transducer	Transmits and receives ultrasonic waves for distance or defect measurement	High precision, nondestructive evaluation	Level measurement, flow monitoring, quality inspection
Thermal Transducer	Detects heat transfer or temperature variation	Stable operation, accurate temperature monitoring	Process control, HVAC systems, furnace monitoring
Flexible/Wearable Transducer	Uses flexible conductive materials for conformable sensing	Lightweight, bendable, wearable design	Human-machine interfaces, healthcare monitoring, smart manufacturing

Smart transducer technologies are maturing quickly, enabling improved system interoperability for industrial measurement and operational intelligence. Modern transducers feature advanced sensing materials, embedded intelligence software, wireless communication and artificial intelligence to provide high-fidelity real-time data, examples of which are used for autonomous process control, real-time predictive maintenance, as well as digital manufacturing. Smart transducers will likely be a key part of intelligent, adaptive and sustainable industrial automation systems as industries continue down the path of Industry 4.0 and Industrial Internet of Things (IIoT) technologies.

5. INDUSTRIAL MEASUREMENT SYSTEMS

Industrial measurement systems are among the most fundamental components of contemporary manufacturing processes, providing timely and accurate quantitative information on process variables which is essential for monitoring, control and optimization. It is an ordered system of components, including sensors, smart transducers and conditioning circuits, data acquisition units, communication networks, controllers and visualization platforms (Imkamp et al., 2016). They are mainly aimed at measuring physical parameters with great accuracy and reliability, including temperature, pressure, flow rate, level, vibration, force, displacement, humidity, and chemical compositions (McMillan & Considine, 1999). Switching to smart digital measurement systems from traditional analog instrumentation has significantly improved the precision of measurements, time response capabilities, operational effectiveness and flexibility in multiple sectors. Industrial measurement systems provide applications of real-time sensing and automatic control methods to guarantee stable production processes and prevent equipment malfunctions, while also ensuring compliance with quality and safety regulations (Tambare et al., 2021).

The organization of modern industrial measurement systems has drastically changed with the introduction of Industry 4.0 technologies [6]. Process data obtained by smart sensors will have its local signal conditioning, filtering, calibration and error compensation performed either on-chip or off-chip (Edgar and Pistikopoulos, 2018) via embedded processors for transmission as digitalized information over time-varying industrial communication networks. This information can be analyzed, and then industrial systems can be controlled automatically by a PLC, DCS, SCADA system or MES. Furthermore, with cloud computing, edge computing, IIoT and AI, these systems can be extended to the realization of predictive maintenance in geographically distributed production facilities along with intelligent fault diagnosis and adaptive process optimization. As such, industries can improve productivity while reducing downtime and ensuring product consistency as well as optimal resource use (Tarek & Paran, 2024).

Measurement systems used in industrial applications include manufacturing chemical processing, oil and gas, power generation, thermal plant optimization (boilers), food processing, pharmaceutical, automobile manufacture, aerospace engine, water treatment and renewable energy. These systems are applied in manufacturing sectors for dimensional measurements, condition monitoring of machine components, robotic control and even quality checking. For example, chemical and pharmaceutical plants continuously monitor pressure, temperature, pH and flow parameters to manage safe process control (Saez et al. 2018). This can be achieved through measurement data with digital twins or industrial analytics for schedules smart factories and intelligent systems in the energy sector for monitoring electrical distribution networks, pipelines and transformers measured by appropriate meters (Yin et al., 2014). The application of measurement systems in the autonomous manufacturing environment is being extended due to robotics and miniaturization technologies [51], artificial intelligence (AI) [12], and wireless communication technology- Internet of Things (IoT): IoT-based wireless sensors can collect data on environmental conditions or status updates without needing a physical connection between sensor nodes.

TABLE 4 Major Components of Industrial Measurement Systems

Component	Primary Function	Common Technologies	Industrial Applications
Smart Sensors	Detect physical, chemical, or environmental parameters	MEMS, optical, capacitive, resistive, piezoelectric sensors	Temperature, pressure, vibration, humidity, gas monitoring
Smart Transducers	Convert physical quantities into digital electrical signals	Fibre-optic, inductive, ultrasonic, electrochemical transducers	Process measurement, machine monitoring, Automation
Signal Conditioning Unit	Amplifies, filters, linearizes, and compensates sensor signals	Operational amplifiers, ADCs, digital filters	Noise reduction and measurement accuracy improvement
Data Acquisition System (DAQ)	Collects and digitizes measurement data	Embedded controllers, DAQ modules	Real-time industrial data collection
Industrial Controllers	Execute monitoring and automatic control algorithms	PLC, DCS, PAC	Manufacturing automation and process control
Communication Network	Transfers measurement data between devices	Ethernet/IP, Modbus, PROFINET, OPC UA, CAN, Wireless IIoT	Industrial communication and remote monitoring
SCADA/HMI System	Visualizes, supervises, and records industrial processes	SCADA software, Human–Machine Interface	Plant supervision and operational management
Edge and Cloud Computing	Stores, processes, and analyzes industrial data	Edge gateways, cloud platforms	Predictive maintenance, AI analytics, digital twin applications

TABLE 5 Key Industrial Parameters Measured Using Smart Measurement Systems

Measured Parameter	Typical Sensor Technology	Industrial Importance	Example Applications
Temperature	RTD, Thermocouple, Thermistor	Process stability and equipment protection	Boilers, furnaces, reactors
Pressure	Piezoresistive, Capacitive	Safety and process control	Hydraulic systems, pipelines
Flow Rate	Ultrasonic, Electromagnetic, Turbine	Resource management and production control	Water treatment, oil and gas
Level	Ultrasonic, Radar, Capacitive	Inventory and storage monitoring	Chemical tanks, silos
Vibration	MEMS Accelerometer, Piezoelectric	Predictive maintenance	Rotating machinery, motors
Displacement	LVDT, Optical Encoder	Precision positioning	CNC machines, robotics
Force and Load	Strain Gauge, Load Cell	Mechanical performance evaluation	Manufacturing and material testing
Humidity	Capacitive, Resistive	Environmental monitoring	Food processing, pharmaceutical production
Gas Concentration	Electrochemical, Optical	Safety and environmental compliance	Chemical industries, mining
Speed and Rotation	Hall Effect, Optical Encoder	Motion control	Motors, conveyor systems, robotics

The future of industrial measurement systems lies in the embedding and integration of intelligent sensing technologies, high-speed communication networks, AI and advanced data analytics. They make it possible to make decisions in real time, to control processes without human intervention, to anticipate faults, and to achieve digital manufacturing, while also boosting operational safety, product quality and energy efficiency. The more advanced the measurement systems become, the more essential they will be in attaining reliable, sustainable and highly automated production processes in an increasingly interconnected industrial environment (Tapia and Elwany, 2014).

6. WIRELESS SENSOR NETWORKS AND INDUSTRIAL INTERNET OF THINGS (IIOT)

Wireless Sensor Networks (WSNs) are becoming an essential enabling technology in the area of smart industrial monitoring, where distributed wireless data and information gathering and delivery operate without a huge wired network infrastructure (Majid et al., 2022). A WSN comprises several sensor nodes capable of measuring physical and environmental status and communicating with a base station via a wireless communication system to coordinate communication and sensing activities using a microcontroller and regulate energy consumption with the support of a power management system. The nodes are connected to gateways or base stations, which collect measurement data and relay it to industrial control systems or cloud-based platforms (Trigka and Dritsas, 2025). Easy installation, low deployment cost, and ease of maintenance for WSNs compared to existing wired monitoring systems make them ideal for use in the following application areas, such as industrial monitoring solutions for large manufacturing facilities, remote industrial facilities, hazardous environments, and Mobile automation systems.

On the other hand, the IIoT is the extension of wireless sensor networks and refers to the ability of smart sensors, intelligent transducers, industrial equipment, controllers, cloud services and analytical platforms to connect into a single digital world (Alabadi et al., 2022). The standardization of communication protocols and interoperability of network architecture enable continuous monitoring of the assets and equipment used in an industrial facility, remote diagnostics, predictive maintenance, energy management, and autonomous optimization. The previously mentioned sophisticated communication technologies such as Wi-Fi, Bluetooth Low Energy (BLE), ZigBee, LoRaWAN, NB-IoT, 5 G and Ethernet-based industrial networks enable secure, high-speed, reliable information flow from field devices to enterprise information systems 12. For instance, IIoT and edge computing reduce it even further because only the data needed for executing a functional task is sent to the cloud; thus decreasing communication latency, which boosts response time while reducing network bandwidth consumption.

WSNs and IIoT have been supported by AI, ML & cloud analytics in an industrial automation scenario. Moreover, intelligent algorithms are trained for the identification of abnormal conditions and equipment wear-out, prediction of equipment failures in real time using limited human interaction so as to optimize production parameters (Noor-A-Rahim et al., 2022). Digital twin technology also adds value to IIoT by using data gathered from the sensors in real time to create a simulation of the behaviour of physical assets, evaluate system performance, and schedule predictive maintenance. These smart features allow for greater production efficiency, reduced downtime, better utilization of resources, and a safer workplace in many industries such as manufacturing, oil and gas, energy, transportation, mining, agriculture and smart infrastructure (Aponte-Luis et al., 2018).

WSN and IIoT offer many advantages, but there are also some technical challenges yet to be overcome through research and development efforts into the future (Farooq et al., 2023). In industrial applications, the challenges associated with limited battery capacity, communication interference, network scalability, heterogeneity of devices, data privacy and security, real-time communication, and the accuracy of data synchronization are important considerations (Abdulhussain et al., 2025). To solve these problems, the researchers are engaged in the development of new technologies, which include energy-efficient communication protocols, secure mechanisms of encryption, blockchain technology used in data management, and self-healing network architectures (Sheng et al., 2015). The industrial automation system of the future will rely on the latest wireless innovations, edge intelligence, digital twins, and autonomous sensing platforms, which will allow for highly resilient, secure, and intelligent manufacturing ecosystems to support fully connected smart factories.

TABLE 6 Comparison of Major Wireless Communication Technologies for IIoT

Communication Technology	Communication Range	Data Rate	Power Consumption	Major Advantages	Typical Industrial Applications
Wi-Fi	50–100 m	Very High	High	High bandwidth, fast communication	Factory automation, machine monitoring
Bluetooth Low Energy (BLE)	10–100 m	Moderate	Very Low	Energy efficient, low-cost deployment	Wearable devices, asset tracking
ZigBee	10–100 m	Low	Very Low	Mesh networking, reliable communication	Building Automation, environmental monitoring
LoRaWAN	2–15 km	Low	Extremely Low	Long-range communication, battery efficiency	Smart agriculture, pipeline monitoring
NB-IoT	Up to 10 km	Low–Moderate	Low	Wide-area coverage, reliable connectivity	Smart metering, utility monitoring
5G	Several kilometers	Very High	Moderate	Ultra-low latency, massive device connectivity	Autonomous manufacturing, robotics
Industrial Ethernet	Wired	Very High	External Power	Deterministic communication, high reliability	PLCs, SCADA, industrial control systems

TABLE 7 Applications of WSNs and IIoT in Industrial Automation

Industrial Sector	Measured Parameters	Smart Sensor Technologies	Benefits of WSN and IIoT
Manufacturing	Temperature, vibration, pressure	MEMS, piezoelectric, optical sensors	Predictive maintenance, quality improvement
Oil and Gas	Pressure, flow, gas leakage	Fibre-optic, ultrasonic, gas sensors	Pipeline monitoring, safety enhancement

Energy and Power	Voltage, current, transformer temperature	Current sensors, thermal sensors	Smart grid management, fault detection
Chemical Industry	pH, pressure, chemical concentration	Electrochemical, capacitive sensors	Process optimization, hazard prevention
Food Processing	Temperature, humidity, contamination	Optical, humidity, biosensors	Quality assurance, regulatory compliance
Healthcare Manufacturing	Cleanroom conditions, environmental monitoring	Particle, humidity, temperature sensors	Product safety and environmental control
Logistics and Warehousing	Location, environmental conditions	RFID, BLE, GPS sensors	Asset tracking, inventory management
Smart Infrastructure	Structural vibration, displacement	Fibre-optic, accelerometers	Structural health monitoring and safety

WSNs together with the Industrial IoT are the driving forces towards a stable technology for intelligent industrial measurement and Automation. The combination of distributed sensing, wireless communication, artificial intelligence, edge computing, and cloud-based analytics among these capabilities allows for real-time asset monitoring, autonomous decision-making, predictive maintenance, and real-time operational optimization. WSNs and IIoT will become increasingly important in smart manufacturing systems that will become fully autonomous and sustainable, as the technologies being developed for communications move into 6G, intelligent edge devices will more and more assist with communication and control, and self-organizing/self-configuring industrial networks will become commonplace.

7. AI AND MACHINE LEARNING IN SMART SENSING

One of the most revolutionary applications that Artificial Intelligence (AI) and Machine Learning (ML) affect smart sensing systems is their ability to assist in intelligent data analysis, autonomous decision-making, and predictive maintenance mechanization from various temperature sensors analyzed by parallel gates using multi-hypothesis Bayesian filtering techniques (Yuan et al., 2024). Conventional sensors only perform the measuring and reporting of data, while smart sensors with AI capability interpret these measurements at their own level to provide AB1NS as well as real-time information towards an industrial control system (ICS) that can alarm abnormal conditions of operation [5]. Machine learning algorithms can identify deeper patterns in the data based on past and present sensor readings, classify equipment health conditions, forecast impending failures of machinery or predict their manufacturing process and optimization (Sharma et al., 2022). Along with machine vision sensor arrays or LSTM and CNN networks, the signals emitted from these sensors which are already inadvertently complex have also been taken to a significant height. And finally, with the machine vision sensor arrays or LSTM and CNN networks, the already complicated sensor signals are strengthened. Moreover, if combined with edge computing concepts, it enhances the efficiency of data communication by analyzing at the local site where they are produced data security and reduced latency are granted (Taheri & Salimi Beni 2025). Recent work has seen applications of smart sensing with AI capability for domains ranging from predictive maintenance, quality inspection and robotics to energy management, structural health monitoring (SHM) and autonomous manufacturing. Despite the above advantages, some essential fields of research are: Limited Datasets for Labelling, Cyber and Security threats, Computational complexity, and interpretability of models (Çınar et al., 2020). The intelligence, reliability, and scalability of future smart sensing systems will continue to be enhanced by continued advancement of explainable AI, federated learning, digital twins, and IIoT.

TABLE 8 AI and ML Techniques in Smart Sensing

AI/ML Technique	Primary Function	Industrial Application	Key Benefits
Artificial Neural Network (ANN)	Pattern recognition and prediction	Process monitoring	High prediction accuracy
Support Vector Machine (SVM)	Fault classification	Machine condition monitoring	Robust classification performance
Random Forest	Predictive analytics	Predictive maintenance	Handles complex industrial datasets
Convolutional Neural Network (CNN)	Image and signal analysis	Visual inspection and defect detection	High feature extraction capability
LSTM	Time-series forecasting	Equipment health monitoring	Accurate sequential data analysis
Reinforcement Learning	Adaptive control	Industrial robotics and Automation	Optimizes operational decisions
Edge AI	Local sensor data processing	Real-time industrial monitoring	Low latency and reduced bandwidth usage

8. EDGE COMPUTING AND DIGITAL TWIN INTEGRATION

Edge computing and digital twins are enabling a kind of help for industrial measurement and Automation to be smarter, faster, and more efficient than ever before. The other approach, called edge computing, deals with processing and analyzing data gathered from the sensors locally rather than only taking care of it through Cloud Computing (Al Zami et al., 2025). Computing locally at the edge minimizes communications latency, lowers bandwidth usage, preserves relative data privacy and facilitates fast decision-making for time-sensitive industrial applications or other situations with communication delay. Advanced sensors with embedded processors can decode sensor signals and even perform feature extraction, anomaly detection, and some initial machine learning inference before relaying pertinent information to supervisory control computers or cloud-based platforms [3]. Besides, this distributed computing is the same technology that could also be used by robots working in manufacturing plants and autonomous vehicles or energy systems and process industries where the safety of response time directly affects performance many times.

Another aspect of digital twin is edge computing as well because the aim was providing real-time visualization of a physical asset, production line or even plant based on data collected by sensors. Since smart sensors and transducers continuously obtain data, the information is sent to a digital twin to simulate how the industrial equipment being monitored behaves in terms of condition and performance (Crespo-Aguado et al., 2024). Such virtual models would allow operators and engineers to access the state of the equipment, predict failure, make decisions on optimization with respect to manufacturing plans, and even predict how changes in operations will impact processes running on that same set of actual equipment without hampering their functioning. Adding the potential of AI and machine learning to digital twin's further increases predictive maintenance capabilities, providing learning opportunities from past and real-time data insights to optimize processes and make optimized decisions, taking advantage of this real-time information (Li et al, 2025).

Considering the use of edge computing and digital twin technology, the combination gives the industrial world a wealth of intelligence and can be leveraged to operate and produce a "smart factory" and "autonomous manufacturing". Through the Edge devices, the measurement data can be rapidly calculated at the devices, and in the digital twin, detailed visualization, simulation, and predictive analysis of complex Industrial systems are possible (Hamza, 2026). In general, this all-in-one solution improves the reliability of the machine, lowers operational expenses, maximizes energy efficiency, and supports sustainable production. But there remain great challenges and issues that need to be overcome, such as seamless integration of heterogeneous devices, synchronization of real-world systems both physical and virtual, Cyber Security, noticeable computational resources, communication protocol standardization, etc. Current research work is centred around the realization and deployment of scalable, secure, flexible digital twin ecosystems that can easily adapt to dynamic changes in Industry4. 0, Digital transmission and next-level factory automation systems, also including the use of edge intelligence, cloud computing for IIoT as well as powerful AI to drive better insight through new communication technology.

9. APPLICATIONS IN INDUSTRIAL AUTOMATION

These advancements have paved the way for an essential role of various smart sensors and transducers in industrial Automation, which is monitoring, measurement and control of manufacturing processes with speed, accuracy and intelligence in real time (Hu et al., 2024). Sensors provide real-time reporting of critical process parameters such as force, vibration, humidity, displacement, flow rate and pressure, allowing systems to be automated with limited human interaction within the desired range. Of course, the integration of smart sensing technologies with a Programmable Logic Controller (PLC), a Supervisory Control and Data Acquisition (SCADA) system, a Distributed Control System (DCS), a Manufacturing Execution System (MES), etc. improves production efficiency; production optimizes product quality; and reduces operational downtime (Kalsoom et al., 2020). Predictive maintenance and fault detection automation increased reliability and availability of industrial equipment.

One of the most apparent smart sensing technology applications is in the domain of predictive maintenance, in which the machine health is monitored by onboard sensors during its operation to detect abnormal operating conditions before equipment failures occur (Pech et al., 2021). Measurement of vibration, acoustic emission, motor current and bearing temperature can all be useful to indicate when an overly worn machine or one that has issues with misalignment, imbalance, lubrication and mechanical faults. These are in turn fed into artificial intelligence and machine learning algorithms to predict the end-of-life of the machinery, enabling maintenance planning and avoiding a huge loss from downtimes and operations costs (Farooq et al., 2023). This will reduce the lifetime of equipment and help ensure continuity in production processes as well as resource use.

Smart sensors play a vital role in industrial robotics and automation systems for manufacturing. Different types of sensors vision, laser proximity, force and inertial measurement unit are used to carry out precise assembly of parts as well as material handling operations; welding, packaging inspection and cooperative operation with high precision level and safety can all be achieved using these responsive machines [11] Abdulhussain et al., 2025. Integrating Computer Numerical Control (CNC) with Flexible Manufacturing Systems enables intelligent sensors to monitor tool wear, spindle vibration and cutting force and dimensional accuracy, which allows the machining parameters to be optimized based on those measurements in order to produce a consistent product. Additionally, utilizing sensor fusion methods that combine data from different sensors enhances the perception abilities of the robot, aiding in robust control and autonomous navigation (Rahman et al., 2025).

Smart sensing systems are also used in a variety of process industries like the chemical industry, pharmaceuticals, food processing, oil/gas industry and power generation to improve safe continuous monitoring for efficient operation of a process by way of measuring the various variables. Sensor data can provide real-time feedback on process and quality control, environmental compliance and workplace safety (Folgado et al., 2024). Thus, IIoT, WSNs, digital twin and edge computing are proposed for improving industrial Automation under remote monitoring through intelligent analytics to increase energy-efficient production and autonomous management of physical assets. To arrive at Industry 4.0 (Kalsoom et al., 2020), smart sensing technologies would continue to be a key component of designing highly connected, intelligent, and sustainable industrial automation systems.

10. CHALLENGES AND LIMITATIONS

With the introduction of numerous advanced technologies such as smart sensors and transducers, great advancement has been made in the development of such sensors, but there are still many problems that must be overcome in both their development and use before they become widespread in industrial Automation. Some of the primary challenges are ongoing accurate and stable measurement of various parameters in difficult industrial environments characterized by high levels of extreme temperature, humidity, EMI, vibration, dust, and corrosive chemicals. The extended operating time could bring about calibration drift, requiring regular maintenance and recalibration for accurate measurements. Furthermore, since there are no universal standards for communications between dissimilar devices, the problem of interoperability between different manufacturers is still a significant issue. Furthermore, if they have a successful integration of modern smart sensing with existing industrial equipment, it can be costly and complex.

As the smart sensors are connected, sharing operational information day in and day out over Industrial Internet of Things (IIoT) networks, cybersecurity has become another critical issue. Uncontrolled access, cyberattacks, the presence of malware, or data manipulation attacks may pose threats to the system and compromise industrial systems. Apart from this, there are other constraints, like limited computational capability, storage, and battery life, with the deployment of intelligent edge devices, especially in wireless sensor networks. Furthermore, the advent of AI also has several challenges relating to algorithmic reliability, data quality, algorithm interpretability, and computational complexity. To overcome these challenges, the industry needs to create strong communication protocols, secure data management strategies, energy-efficient hardware, standardized architectures, and explainable AI techniques that guarantee reliable and scalable industrial sensing solutions.

11. FUTURE RESEARCH DIRECTIONS

Further research on smart sensors and transducers will be directed towards the creation of the most intelligent and autonomous energy-efficient sensing systems that are able to support next-generation industrial Automation. Nanotechnology and flexible electronics, MEMS, NEMS and advanced functional materials will make it possible to produce more sensitive, smaller, and highly durable sensors, which will be able to measure more accurately and consume less power. It is believed that the self-powered sensors powered by energy harvesting technologies can further reduce the need for traditional batteries and enable long operation time. In addition, sensors will include multimodal sensor fusion, which will increase the accuracy of the measurements, since multiple types of sensors will be used to gauge all aspects of the industry.

AI will continue to be a key enabler for smart sensing in the future, providing full autonomy to perform calibration, intelligent fault detection and predictive decision making, and moving it to the edge, thus enabling adaptive learning. The future applications for industrial systems are predicted to be driven by Edge Computing, Digital Twins, the IIoT, and cloud computing & 6G communication technologies, which are expected to create highly interconnected industrial systems that are self-optimizing. Research will also largely center on cybersecurity, as well as data integrity issues related to blockchain technology, interoperability of communication protocols, explainable AI, and privacy-enhancing machine learning to ensure secure and reliable industrial processes. The technological advances will enable the fulfilment of the ever-increasing demand of modern industrial manufacturing towards completely independent smart factories which are resilient, sustainable and far advanced in industrial digitalization.

12. CONCLUSION

Smart sensors and transducers are the backbone of modern industrial measurement and automation systems, which provide accurate data gathering, intelligent monitoring, and autonomous process control. This points to the great development of sensing technologies such as MEMS, NEMS, fibre-optic sensors, wireless sensor networks, and intelligent transducers, improving the accuracy, reliability, and efficiency of measurement in a variety of industrial applications. Even traditional sensing systems have been converted into intelligent platforms for predictive maintenance, real-time fault diagnosis, adaptive decision-making and process optimization with the integration of other emerging technologies like Artificial Intelligence AI, ML, edge computing, digital twins and even the IIoT. Rapid development of smart factories brought by these technologies has led to greater machine utilization, reduced operating costs, improved product quality and sustainable manufacturing.

Nevertheless, the widespread adoption of intelligent sensing systems in more complex industrial environments is limited by several challenges, including interoperability and cybersecurity aspects; communication reliability; energy efficiency level depending on use cases; and lack of standards metabolism among heterogeneous devices to enable system scalability. To tackle these challenges, further interdisciplinary research is required spanning advanced materials, embedded intelligence and secure communication protocols alongside explainable artificial intelligence and next-generation wireless technologies. There is a growing need to enable resilient, efficient, and sustainable manufacturing through a growing level of industrial Automation, where autonomous, self-learning, and interconnected sensing ecosystems are increasingly based on intelligent sensors, edge intelligence, cloud computing, and digital twins. Overall, the developments in smart sensors and transducers are very promising in terms of the technology that will enable the realization of Industry 4.0 and future smart manufacturing systems, with their potential opportunities for innovation and productivity improvement and for digital transformation across industries worldwide.

REFERENCES

[1] S. H. Abdulhussain et al., "A Comprehensive Review of Sensor Technologies in IoT: Technical Aspects, Challenges, and Future Directions," Computers, vol. 14, no. 8, pp. 342–342, Aug. 2025, doi: 10.3390/computers14080342.

[2] R. Agrifoglio, C. Cannavale, E. Laurenza, and C. Metallo, "How emerging digital technologies affect operations management through cocreation. Empirical evidence from the maritime industry," Production Planning & Control, vol. 28, no. 16, pp. 1298–1306, Oct. 2017, doi: 10.1080/09537287.2017.1375150.

[3] M. Bokhtiar Al Zami, S. Shaon, V. Khanh Quy, and D. C. Nguyen, "Digital Twin in Industries: A Comprehensive Survey," IEEE Access, vol. 13, pp. 47291–47336, 2025, doi: 10.1109/access.2025.3551532.

[4] M. Alabadi, A. Habbal, and X. Wei, "Industrial Internet of Things: Requirements, Architecture, Challenges, and Future Research Directions," IEEE Access, vol. 10, pp. 66374–66400, 2022, doi: 10.1109/access.2022.3185049.

[5] Y. M. Alginahi, O. Sabri, and W. Said, "Reinforcement Learning for Industrial Automation: A Comprehensive Review of Adaptive Control and Decision-Making in Smart Factories," Machines, vol. 13, no. 12, p. 1140, Dec. 2025, doi: 10.3390/machines13121140.

[6] J. Aponte-Luis, J. Gómez-Galán, F. Gómez-Bravo, M. Sánchez-Raya, J. Alcina-Espigado, and P. Teixido-Rovira, "An Efficient Wireless Sensor Network for Industrial Monitoring and Control," Sensors, vol. 18, no. 2, p. 182, Jan. 2018, doi: 10.3390/s18010182.

[7] Heni Belgacem and Inès Chihi, "Toward Reliable and Intelligent Sensor Systems: A Comprehensive Study of Fault Diagnosis and Mitigation," IEEE Sensors Reviews, pp. 1–27, Jan. 2025, doi: 10.1109/sr.2025.3601092.

[8] G. B. Benitez, N. F. Ayala, and A. G. Frank, "Industry 4.0 innovation ecosystems: An evolutionary perspective on value cocreation," International Journal of Production Economics, vol. 228, p. 107735, Oct. 2020, doi: 10.1016/j.ijpe.2020.107735.

[9] Z. Bi, L. Da Xu, and C. Wang, "Internet of Things for Enterprise Systems of Modern Manufacturing," IEEE Transactions on Industrial Informatics, vol. 10, no. 2, pp. 1537–1546, May 2014, doi: 10.1109/tii.2014.2300338.

[10] L. Bibby and B. Dehe, "Defining and assessing industry 4.0 maturity levels – case of the defence sector," Production Planning & Control, vol. 29, no. 12, pp. 1030–1043, Sept. 2018, doi: 10.1080/09537287.2018.1503355.

[11] Burke, R.; Mussomeli, A.; Laaper, S.; Hartigan, M.; Sniderman, B. The smart factory. Responsive, adaptive, connected manufacturing. Deloitte 2014, 31, 1–10.

[12] J. L. C. Choy, J. Wu, C. Long, and Y.-B. Lin, "Ubiquitous and Low Power Vehicles Speed Monitoring for Intelligent Transport Systems," IEEE Sensors Journal, vol. 20, no. 11, pp. 5656–5665, June 2020, doi: 10.1109/jsen.2020.2974829.

[13] Z. M. Çınar, A. A. Nuhu, Q. Zeeshan, O. Korhan, M. Asmael, and B. Safaei, "Machine Learning in Predictive Maintenance towards Sustainable Smart Manufacturing in Industry 4.0," Sustainability, vol. 12, no. 19, p. 8211, Oct. 2020, doi: 10.3390/su12198211.

[14] M. Crespo-Aguado, R. Lozano, F. Hernandez-Gobertti, N. Molner, and D. Gomez-Barquero, "Flexible Hyper-Distributed IoT–Edge–Cloud Platform for Real-Time Digital Twin Applications on 6G-Intended Testbeds for Logistics and Industry," Future Internet, vol. 16, no. 11, p. 431, Nov. 2024, doi: 10.3390/fi16110431.

[15] B. Dahlin, "Size Matters: Problems and Advantages Associated with Highly Miniaturized Sensors," Sensors, vol. 12, no. 3, pp. 3018–3036, Mar. 2012, doi: 10.3390/s120303018.

[16] L. S. Dalenogare, G. B. Benitez, N. F. Ayala, and A. G. Frank, "The expected contribution of Industry 4.0 technologies for industrial performance," International Journal of Production Economics, vol. 204, no. 1, pp. 383–394, Oct. 2018, doi: 10.1016/j.ijpe.2018.08.019.

[17] Spyridon Daousis, Nikolaos Peladarinos, Vasileios Cheimaras, Panagiotis Papageorgas, D. D Piromalis, and Radu Adrian Munteanu, "Overview of Protocols and Standards for Wireless Sensor Networks in Critical Infrastructures," Future Internet, vol. 16, no. 1, pp. 33–33, Jan. 2024, doi: 10.3390/fi16010033.

[18] Md. Shezad Dihan et al., “Digital Twin: Data Exploration, Architecture, Implementation and Future,” Heliyon, vol. 10, no. 5, pp. e26503-e26503, Feb. 2024, doi: 10.1016/j.heliyon.2024.e26503.

[19] Dodia, P. Shah, R. Sekhar, and M. D, "Smart Sensors in Industry 4.0," 2023 4th International Conference for Emerging Technology (INCET), pp. 1–6, May 2023, doi: 10.1109/incet57972.2023.10170282.

[20] T. F. Edgar and E. N. Pistikopoulos, "Smart manufacturing and energy systems," Computers & Chemical Engineering, vol. 114, pp. 130–144, June 2018, doi: 10.1016/j.compchemeng.2017.10.027.

[21] H. Farhangi, "Smart Grid," Encyclopedia of Sustainable Technologies, pp. 195–203, 2017, doi: 10.1016/b978-0-12-409548-9.10135-6.

[22] Muhammad Shoaib Farooq et al., "A Survey on the Role of Industrial IoT in Manufacturing for Implementation of Smart Industry," Sensors, vol. 23, no. 21, pp. 8958–8958, Nov. 2023, doi: 10.3390/s23218958.

[23] Ficili, M. Giacobbe, G. Tricomi, and A. Puliafito, "From Sensors to Data Intelligence: Leveraging IoT, Cloud, and Edge Computing with AI," Sensors, vol. 25, no. 6, pp. 1763–1763, Mar. 2025, doi: 10.3390/s25061763.

[24] F. J. Folgado, D. Calderón, I. González, and A. J. Calderón, "Review of Industry 4.0 from the Perspective of Automation and Supervision Systems: Definitions, Architectures and Recent Trends," Electronics, vol. 13, no. 4, p. 782, Jan. 2024, doi: 10.3390/electronics13040782.

[25] G. Frank, L. S. Dalenogare, and N. F. Ayala, "Industry 4.0 technologies: Implementation patterns in manufacturing companies," International Journal of Production Economics, vol. 210, no. 8, pp. 15–26, Apr. 2019, doi: https://doi.org/10.1016/j.ijpe.2019.01.004.

[26] Salimi Lafmejani, M. Tale Masouleh, and A. Kalhor, "Trajectory tracking control of a pneumatically actuated 6-DOF Gough–Stewart parallel robot using Backstepping-Sliding Mode controller and geometry-based quasi forward kinematic method," Robotics and Computer-Integrated Manufacturing, vol. 54, pp. 96–114, Dec. 2018, doi: 10.1016/j.rcim.2018.06.001.

[27] L. S. Goecks, A. F. Habekost, A. M. Coruzzolo, and M. A. Sellitto, "Industry 4.0 and Smart Systems in Manufacturing: Guidelines for the Implementation of a Smart Statistical Process Control," Applied System Innovation, vol. 7, no. 2, p. 24, Apr. 2024, doi: 10.3390/asi7020024.

[28] M. F. Hamza, "Cloud, Edge, and Digital Twin Architectures for Condition Monitoring of Computer Numerical Control Machine Tools: A Systematic Review," Information, vol. 17, no. 2, p. 153, Feb. 2026, doi: 10.3390/info17020153.

[29] Herrojo, Paredes, Mata-Contreras, and Martín, "Chipless-RFID: A Review and Recent Developments," Sensors, vol. 19, no. 15, p. 3385, Aug. 2019, doi: 10.3390/s19153385.

[30] Y. Hu et al., "Industrial Internet of Things Intelligence Empowering Smart Manufacturing: A Literature Review," IEEE Internet of Things Journal, vol. 11, no. 11, pp. 1–1, Jan. 2024, doi: 10.1109/jiot.2024.3367692.

[31] D. Imkamp et al., "Challenges and trends in manufacturing measurement technology – the 'Industrie 4.0' concept," Journal of Sensors and Sensor Systems, vol. 5, no. 2, pp. 325–335, Oct. 2016, doi: 10.5194/jsss-5-325-2016.

[32] D. Ivanov, A. Dolgui, B. Sokolov, F. Werner, and M. Ivanova, "A dynamic model and an algorithm for short-term supply chain scheduling in the smart factory industry 4.0," International Journal of Production Research, vol. 54, no. 2, pp. 386–402, Jan. 2015, doi: 10.1080/00207543.2014.999958.

[33] Jeon, J.-S., Yoon, J. Um, and S.-H. Suh, "The architecture development of Industry 4.0 compliant smart machine tool system (SMTS)," Journal of Intelligent Manufacturing, vol. 31, no. 8, pp. 1837–1859, Jan. 2020, doi: 10.1007/s10845-020-01539-4.

[34] T. Kalsoom, N. Ramzan, S. Ahmed, and M. Ur-Rehman, "Advances in Sensor Technologies in the Era of Smart Factory and Industry 4.0," Sensors, vol. 20, no. 23, p. 6783, Nov. 2020, doi: 10.3390/s20236783.

[35] Y. A. Alsultanny and F. M. Alnassar, "Evaluating Factors Motivate Users on Green IT Readiness (Part 2)," International Journal of Green Computing, vol. 8, no. 1, pp. 23–35, Jan. 2017, doi: 10.4018/ijgc.2017010102.

[36] Kim, H. Cho, S.-I. Han, A. Han, and K.-H. Han, "A disposable microfluidic flow sensor with a reusable sensing substrate," Sensors and Actuators B: Chemical, vol. 288, pp. 147–154, June 2019, doi: 10.1016/j.snb.2019.02.088.

[37] Kimani, V. Oduol, and K. Langat, "Cyber Security Challenges for IoT-based Smart Grid Networks," International Journal of Critical Infrastructure Protection, vol. 25, no. 2, pp. 36–49, June 2019.

[38] N. V. Kirianaki, S. Y. Yurish, N. O. Shpak, and V. P. Deynega, "Data Acquisition and Signal Processing for Smart Sensors," Mar. 2002, doi: 10.1002/0470846100.

[39] H. Landaluce, L. Arjona, A. Perallos, F. Falcone, I. Angulo, and F. Muralter, "A Review of IoT Sensing Applications and Challenges Using RFID and Wireless Sensor Networks," Sensors, vol. 20, no. 9, p. 2495, Apr. 2020, doi: 10.3390/s20092495.

[40] N. Le, L. Le Tuan, and M. N. Dang Tuan, "Smart-building management system: An Internet-of-Things (IoT) application business model in Vietnam," Technological Forecasting and Social Change, vol. 141, pp. 22–35, Apr. 2019, doi: 10.1016/j.techfore.2019.01.002.

[41] J. Li, F. Xing, D. Chu, and Z. Liu, "High-Accuracy Self-Calibration for Smart, Optical Orbiting Payloads Integrated with Attitude and Position Determination," Sensors, vol. 16, no. 8, p. 1176, July 2016, doi: 10.3390/s16081176.

[42] Z. Li et al., "A reference framework for the digital twin smart factory based on cloud-fog-edge computing collaboration," Journal of Intelligent Manufacturing, vol. 36, no. 5, pp. 3625–3645, June 2024, doi: 10.1007/s10845-024-02424-0.

[43] H. Lightfoot, T. Baines, and P. Smart, "The servitization of manufacturing," International Journal of Operations & Production Management, vol. 33, no. 11/12, pp. 1408–1434, Nov. 2013, doi: 10.1108/ijopm-07-2010-0196.

[44] Majid et al., "Applications of Wireless Sensor Networks and Internet of Things Frameworks in the Industry Revolution 4.0: A Systematic Literature Review," Sensors, vol. 22, no. 6, p. 2087, Mar. 2022, doi: 10.3390/s22062087.

[45] Manavalan and K. Jayakrishna, "A review of Internet of Things (IoT) embedded sustainable supply chain for Industry 4.0 requirements," Computers & Industrial Engineering, vol. 127, no. 1, pp. 925–953, Jan. 2019, doi: 10.1016/j.cie.2018.11.030.

[46] C. Matta, S. Pinna, S. Ortu, F. Parodo, D. Giusto, and M. Anedda, "A Survey on IoT-Based Smart Electrical Systems: An Analysis of Standards, Security, and Applications," Energies, vol. 19, no. 4, p. 965, Feb. 2026, doi: 10.3390/en19040965.

[47] G. K. McMillan and D. Considine, Process/Industrial Instruments and Controls Handbook, 5th Edition. McGraw Hill Professional, 1999.

[48] Morchid, Z. Said, A. Y. Abdelaziz, P. Siano, and H. Qjidaa, "Fuzzy Logic-Based IoT System for Optimizing Irrigation with Cloud Computing: Enhancing Water Sustainability in Smart Agriculture," Smart Agricultural Technology, p. 100979, Apr. 2025, doi: 10.1016/j.atech.2025.100979.

[49] V. Mulloni and M. Donelli, "Chipless RFID Sensors for the Internet of Things: Challenges and Opportunities," Sensors, vol. 20, no. 7, p. 2135, Apr. 2020, doi: 10.3390/s20072135.

[50] S. Han and J. Xing, "Ensuring data storage security through a novel third party auditor scheme in cloud computing," 2011 IEEE International Conference on Cloud Computing and Intelligence Systems, pp. 264–268, Sept. 2011, doi: 10.1109/ccis.2011.6045072.

[51] Noor-A-Rahim et al., "Wireless Communications for Smart Manufacturing and Industrial IoT: Existing Technologies, 5G and Beyond," Sensors, vol. 23, no. 1, p. 73, Jan. 2023, doi: 10.3390/s23010073.

[52] O. Val, O. O. Olaniyi, O. Selesi-Aina, M. O. Gbadebo, and T. M. Kolade, "Machine Learning-enabled Smart Sensors for Real-time Industrial Monitoring: Revolutionizing Predictive Analytics and Decision-making in Diverse Sector," Asian Journal of Research in Computer Science, vol. 17, no. 11, pp. 92–113, Nov. 2024, doi: 10.9734/ajrcos/2024/v17i11522.

[53] S. Pandey, M. Chaudhary, and Z. Tóth, "An investigation on real-time insights: enhancing process control with IoT-enabled sensor networks," Discover Internet of Things, vol. 5, no. 1, Mar. 2025, doi: 10.1007/s43926-025-00124-6.

[54] H. Rawat and Y. Pathak, "Smart Sensors: Analyzing Efficiency of Smart Sensors in Public Domain," SSRN Electronic Journal, 2019, doi: 10.2139/ssrn.3517663.
[55] M. Pech, J. Vrchota, and J. Bednář, "Predictive Maintenance and Intelligent Sensors in Smart Factory: Review," Sensors, vol. 21, no. 4, p. 1470, Feb. 2021, doi: 10.3390/s21041470.
[56] Punithavathi, S. Geetha, M. Karuppiah, S. H. Islam, M. M. Hassan, and K.-K. R. Choo, "A lightweight machine learning-based authentication framework for smart IoT devices," Information Sciences, vol. 484, pp. 255–268, May 2019, doi: 10.1016/j.ins.2019.01.073.
[57] M. A. Rahman, M. F. Shahrior, K. Iqbal, and A. A. Abushaiba, "Enabling Intelligent Industrial Automation: A Review of Machine Learning Applications with Digital Twin and Edge AI Integration," Automation, vol. 6, no. 3, p. 37, Aug. 2025, doi: 10.3390/automation6030037.
[58] R. Rakholia, A. L. Suárez-Cetrulo, M. Singh, and R. S. Carbajo, "Advancing Manufacturing Through Artificial Intelligence: Current Landscape, Perspectives, Best Practices, Challenges and Future Direction," IEEE Access, pp. 1–1, 2024, doi: 10.1109/access.2024.3458830.
[59] M. Saez, F. P. Maturana, K. Barton, and D. M. Tilbury, "Real-Time Manufacturing Machine and System Performance Monitoring Using Internet of Things," IEEE Transactions on Automation Science and Engineering, vol. 15, no. 4, pp. 1735–1748, Oct. 2018, doi: 10.1109/tase.2017.2784826.
[60] Sharma et al., "Recent Trends in AI-Based Intelligent Sensing," Electronics, vol. 11, no. 10, p. 1661, May 2022, doi: 10.3390/electronics11101661.
[61] R. Sharma, "Enhancing Industrial Automation and Safety Through Real-Time Monitoring and Control Systems," International Journal on Smart & Sustainable Intelligent Computing, vol. 1, no. 2, pp. 1–20, Oct. 2024, doi: 10.63503/j.ijssic.2024.30.
[62] Z. Sheng, C. Mahapatra, C. Zhu, and V. C. M. Leung, "Recent Advances in Industrial Wireless Sensor Networks Toward Efficient Management in IoT," IEEE Access, vol. 3, pp. 622–637, 2015, doi: 10.1109/access.2015.2435000.
[63] M. Shkel, "Smart MEMS: micro-structures with error-suppression and self-calibration control capabilities," Proceedings of the 2001 American Control Conference. (Cat. No.01CH37148), pp. 1208–1213 vol.2, 2001, doi: 10.1109/acc.2001.945886.
[64] Shrouf, J. Ordieres, and G. Miragliotta, "Smart factories in Industry 4.0: A review of the concept and of energy management approaches in production based on the Internet of Things paradigm," 2014 IEEE International Conference on Industrial Engineering and Engineering Management, Dec. 2014, doi: 10.1109/ieem.2014.7058728.
[65] Arvindan Sivasuriyan et al., "Emerging Trends in the Integration of Smart Sensor Technologies in Structural Health Monitoring: A Contemporary Perspective," Sensors, vol. 24, no. 24, pp. 8161–8161, Dec. 2024, doi: 10.3390/s24248161.
[66] H. Taheri and A. Salimi Beni, "Artificial Intelligence, Machine Learning, and Smart Technologies for Nondestructive Evaluation," Handbook of Nondestructive Evaluation 4.0, pp. 853–881, 2025, doi: 10.1007/978-3-031-84477-5_70.
[67] Tambare, C. Meshram, C.-C. Lee, R. J. Ramteke, and A. L. Imoize, "Performance Measurement System and Quality Management in Data-Driven Industry 4.0: a Review," Sensors, vol. 22, no. 1, p. 224, Dec. 2021.
[68] V. Tanyingyong, R. Olsson, J. Cho, M. Hidell, and P. Sjodin, "IoT-Grid: IoT Communication for Smart DC Grids," 2016 IEEE Global Communications Conference (GLOBECOM), pp. 1–7, Dec. 2016, doi: 10.1109/glocom.2016.7841917.
[69] Tapia and A. Elwany, "A Review on Process Monitoring and Control in Metal-Based Additive Manufacturing," Journal of Manufacturing Science and Engineering, vol. 136, no. 6, Oct. 2014, doi: 10.1115/1.4028540.
[70] J. H. Tarek and M. S. Paran, "QUANTITATIVE ASSESSMENT OF AUTOMATION AND CONTROL STRATEGIES FOR PERFORMANCE OPTIMIZATION IN U.S. INDUSTRIAL PLANTS," ASRC Procedia: Global Perspectives in Science and Scholarship, vol. 04, no. 01, pp. 169–205, Jan. 2024, doi: 10.63125/eqfz8220.
[71] Ziba Torkashvand, Farzaneh Shayeganfar, and A. Ramazani, "Nanomaterials Based Micro/Nanoelectromechanical System (MEMS and NEMS) Devices," Micromachines, vol. 15, no. 2, pp. 175–175, Jan. 2024, doi: 10.3390/mi15020175.
[72] M. Trigka and E. Dritsas, "Wireless Sensor Networks: From Fundamentals and Applications to Innovations and Future Trends," IEEE Access, vol. 13, pp. 96365–96399, 2025, doi: 10.1109/access.2025.3572328.
[73] Y.-C. Tsai, P.-C. Huang, and C.-L. Dai, "Editorial for the Special Issue on MEMS/NEMS Devices and Applications, 2nd Edition," Micromachines, vol. 16, no. 2, p. 189, Feb. 2025, doi: 10.3390/mi16020189.
[74] K. P. Uvarajan, "Vibration Analysis of Smart Structures Integrated with Embedded Piezoelectric Sensor Networks: A Comprehensive Review," Journal of Reconfigurable Hardware Architectures and Embedded Systems, pp. 18–29, 2024, Accessed: Aug. 10, 2026. [Online]. Available: https://fsrap.com/index.php/JRHAES/article/view/3
[75] M. Wilkesmann and U. Wilkesmann, "Industry 4.0 – organizing routines or innovations?," VINE Journal of Information and Knowledge Management Systems, vol. 48, no. 2, pp. 238–254, May 2018, doi: 10.1108/vjikms-04-2017-0019.
[76] Xu, W. Yu, D. Griffith, and N. Golmie, "A Survey on Industrial Internet of Things: A Cyber-Physical Systems Perspective," IEEE Access, vol. 6, pp. 78238–78259, 2018, doi: 10.1109/access.2018.2884906.
[77] M. Xu et al., "Toward Engineering a Secure Android Ecosystem," ACM Computing Surveys, vol. 49, no. 2, pp. 1–47, Nov. 2016, doi: 10.1145/2963145.
[78] Xue, P. Xue, Z. Wang, and H. Ma, "Artificial Intelligence for Cybersecurity in IoT-Edge Systems: A Structured Review of Methods, Datasets, Evaluation, and Deployment Challenges," Electronics, vol. 15, no. 11, p. 2409, June 2026, doi: 10.3390/electronics15112409.
[79] Yin, S. X., Ding, X., Xie, and H. Luo, "A Review on Basic Data-Driven Approaches for Industrial Process Monitoring," IEEE Transactions on Industrial Electronics, vol. 61, no. 11, pp. 6418–6428, Nov. 2014, doi: 10.1109/TIE.2014.2301773.
[80] S.M. Yuan, Z.-W. Hong, and W.-K. Cheng, "Artificial Intelligence and Deep Learning in Sensors and Applications," Sensors, vol. 24, no. 10, p. 3258, May 2024, doi: 10.3390/s24103258.
[81] Z. Zhang, X. Liu, H. Zhou, S. Xu, and C. Lee, "Advances in Machine-Learning Enhanced Nanosensors: From Cloud Artificial Intelligence Toward Future Edge Computing at Chip Level," Small Structures, Dec. 2023, doi: 10.1002/sstr.202300325.
[82] Zuo, Y., Dou, X., Chang, Y., Chen, and C. Ma, "Design and Performance Analysis of a Multilayer Sea Ice Temperature Sensor Used in Polar Region," Sensors, vol. 18, no. 12, p. 4467, Dec. 2018, doi: 10.3390/s18124467.