Two-Dimensional Transformation of a Conventional Manufacturer into a Smart Manufacturer: Architectonic Design, Maintenance Strategies and Applications

Maryam Abdulhakeem Hailan [*], Baraa M. Albaker[**], Muwafaq Shyaa Alwan[***]

,,*** College of Engineering, Al-Iraqia University, Saba'a Abkar Compex, Baghdad, Iraq*

Abstract

Today, Internet of Things (IoT) plays an important role in emerging industries. Due to that, it is considered as a major focus for research in academic and industrial fields in recent years. The Industrial Internet of Things (IIoT) is an assembly of industrial automation, control systems, and Internet of Things (IoT) systems. The broad goals of IIoT can increase work efficiency and productivity, improving asset management through product customization, intelligent monitoring of production applications, and preventive and predictive maintenance of industrial equipment. This article provides a comprehensive list of up-to-date researches carried to transform conventional manufacturers into smart manufacturers by focusing on the two-dimensional dominant key enabling technologies, IIoT and Artificial Intelligence (AI). An IIoT-based generic hieratical architecture is proposed for a smart manufacturer to handle different manufacturer tasks and communication protocols. In addition, current industrial maintenance goals and strategies with major application domains in the transformation to industry 4.0 are carried out.

Keywords- Industry 4.0, Internet of things, artificial intelligence, smart manufacturers, IIoT, hierarchical architecture.

I. INTRODUCTION

Due to the Internet of Things (IoT) rising popularity, interconnected infrastructures with more flexibility and efficiency are being investigated for industry 4.0. Industrial Internet of Things (IIoT) enables remote monitoring of a variety of industrial activities. It is a new word that has emerged as a result of the deployment of IoT in industry 4.0 [1]. Because the IIoT involves a huge number of diverse devices, data interoperability is the most difficult aspect of enabling smooth real-time connectivity. To accomplish data interoperability, several IoT application layer protocols must be integrated. Industry 4.0 is a brand-new environment where advanced high-level sensor acquisition and awareness, data processing, cloud-hosted computing, software development, and Artificial Intelligence (AI) are all united. These provide a thorough, cutting-edge solution for any industrial application, crucial to make sure that a smart factory functions properly. Distributed control system (DCS) are used in IIoT to enable a higher level of automation through the use of cloud computing, big data analysis, AI, and robots to optimize and improve process controls [2].
Misra et al. [3] presented an overview of the IoT, big data, and AI with their role in agri-food systems' future**.** Singh and Rathore [4] developed a Blockchain-enabled smart IoT architecture using AI Technology that enables the effective convergence of blockchain and AI for IoT with existing and recent applications and techniques. Emil and Simon [5] described extensive survey and analysis on the prevalence of AI and IoT in manufacturing SMEs, as well as present limitations and prospects for allowing predictive analytics. The aim of this paper is to propose a new generic architecture based on IIoT to transform into the smart manufacturer with a clear analysis. Also, to list out all industrial maintenance goals and strategies. Also, presents the latest researches and applications in industry 4.0 and the role of IIoT and artificial intelligence in industrial development.

II. GENERIC IIOT ARCHITECTURE

It's In many application contexts, architecture is an abstracted high-level explanation that aids in the identification of issues and challenges. Modularity, extensibility, scalability, and interoperability among heterogeneous devices employing different technologies must all be taken into account and prioritized when developing an IIoT architecture.

Based on Industry 4.0 reference models, an architecture for the Industrial IoT Environments is proposed in this paper. The proposal is based on heretical architecture of four layers including physical layer for field devices, network and communication for gateways and wire- and wireless communication links, a middleware for context-aware, business logic and services provider according to industrial devices or nodes, and the application layer that acts as an interface with an operator. Figure 1 shows the proposed industrial internet of things architecture. Each layer of the architecture is explained in detail in the subsequent sections.

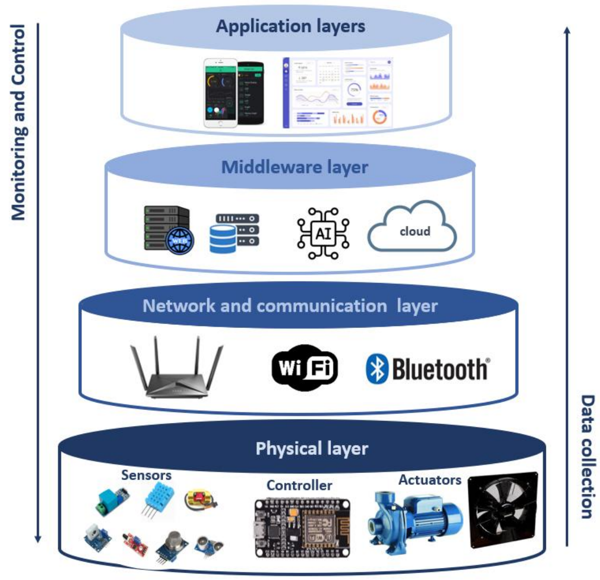

Figure 1:The proposed Industrial Internet of Things (IIoT) architecture

A. Physical Layer

Physical devices including programmable logic controllers (PLCs), sensors, and actuators specific to an industrial environment are considered at this level. The physical devices are connected using a particular data channel to send and receive data. The layer holds the sensors and collects data in real-time by reading the sensors that are attached to them and sending them to the IoT Gateway. Figure2 shows main components embedded in the physical layer.

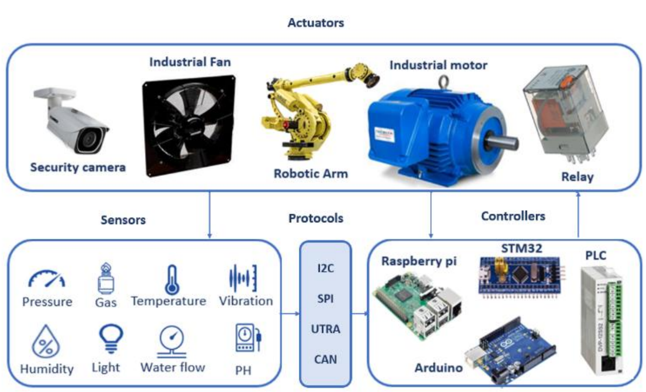

Figure 2: Physical layer components

A.1 Sensors

Any amount, quality, or condition from the physical world may be detected by a sensor, which measures their values and transform it into a discrete in amplitude and discrete in time signal. An input stimulus may employ motion, acceleration, speed, heading, force, pressure, flow, heat, light, moisture, or any other industrial or environmental phenomena. A signal in electric form, such as current, voltage, frequency, capacitance, resistance, etc., is frequently used as the response's output, which is transformed to a readable display or sent across a network for reading, processing, context aware, abstraction, or other distribution.

A.2 Controller

Single Board Computers (SBCs) are computers that contain all of their communication and control options on a single PCB board. SBCs are developed to be portable and low power. Recent popular SBCs include the TMS microcontrollers, Arduino, Nvidia, Raspberry Pi, Azus Tinker Board, Beagle Bone, etc. [6].

Programmable Logic Controllers (PLCs) are used to control the vast majority of industrial actuators. The mass of industrial sensors and actuators are monitored and controlled by PLC-based circuits. PLC Controller gathers data from sensors and tracking devices. Sensors can be connected to the controller directly via the built-in digital and analog input interfaces, or by wired serial communication connectors such as I2C, SPI, UART, RS232, RS485, USB and CAN. The data obtained by these sensors is processed locally in accordance with the system under control algorithm. Some sensors can only communicate with the controller through protocols. Several wired and wireless IoT protocols are currently exists including, Wi-Fi, Zigbee, Z-wave, Bluetooth, RF, PAN, GPRS, LTE, 3/4/5G, NFC, USB, UART, USART, RS-232, RS-485, i2c, SPI, Ethernet, etc. Table 1 depicts the characteristics of the commonly used wired IoT protocols.

Table 1:Characteristics of IoT protocols

Protocols	Main characteristics	Ref
Inter Integrated Circuit (I2C)	• Provides real-time clock control interface. • Utilizes different speed of 100kbps, 400kbps, and 3.4Mbps.	[6][7]
Serial Peripheral Interface (SPI)	• Operates mainly on synchronous serial communication. • Provides short distance communication, chip-to-chip connections between PCBs. • Provides data rate of 20Mb/s up to 100Mbps.	[6][8]
Universal Asynchronous Receiver/Transmitter (UART)	• Serial communication • Allows two heterogenous components on a system to communicate with each another without need for a clock.	[9]

A.3 Actuators

Actuators are devices that conduct actions depending on sensor readings and needed requirements that vary from one application to another. An energy source and a control signal are required for an actuator to operate successfully. Various kinds of actuators are already used in the industries such as relays, motors, cooling/heating devices, etc. The following lists the commonly used types of actuators according to its control mechanism, as depicted in Figure3.

- Electrical actuators are devices that transform energy into mechanical torque and are powered by motors. The torque generated is utilized for controlling specific equipment. They are also utilized to regulate various valves in engines.
- Mechanical actuators are used to convert rotary motion to linear motion. Screws and chains are among the devices used in this conversion. The "screw" is the most basic type of mechanical liner actuator, with ball screw, leadscrew, roller screw, and screw jack actuators all working in a same way. The operating principle is that when the actuator's nut is rotated, shaft moves in a straight line.

- Hydraulic actuators are utilized on quarter-turn and linear valves. Their working principle are implemented in accordance with Pascal's law. When the pressure in a confined incompressible fluid rises at any place in the container, the pressure rises equally everywhere else. Hydraulic actuators are designed with a fluid motor or a cylinder, which employs hydraulic power to achieve a dedicated mechanical task. An oscillatory, linear, or rotational motion is the resultant output.
- Pneumatic actuators are used similar to hydraulic actuators but instead of liquid, compressed gas is employed.

Figure 3:Types of actuators

B. Network and Communication Layer

Network and communication layer, also called communication layer or transmission layer, establishes connectivity between edge devices and the cloud datacenter. It is incorporated in the architecture development to gather data from sensors, actuators and controllers connected to the data channel and save it in the IIoT system's memory before transmitting it to the higher level. In addition, it is used to transmit data from the system's memory to the data channel when new control command is received from the higher level. Insofar as the data channel may be utilized, the information flow is bidirectional to obtain values from various sensors or to send control to actuators attached to the data channel. The layer may have several types of connectivity networks, such as WiFi/IEEE 802.15.4 and Bluetooth, and they are responsible for conveying information to the following layers.

Wireless or wired technology can be used as the communication medium [10]. Wired networks are the ideal option when nodes in the environment are stationary, have a high data transmission need, and handle trustworthy data. For these reasons, the majority of IIoT systems offer wired communication [6]. The communication between the physical layer and the middleware can be accomplished in two ways**:**

- Gateways, which conduct communication protocol and perform IoT data encryption and decryption processes.
- TCP or UDP/IP stack

Additionally, the layer is responsible for interconnecting networks, networks' devices, and intelligent objects. IIoT uses alternative protocols than those that are now in use. As a result, new protocols including MQTT, IEEE, CoAP, mDNS, DNS-SD, and many more have developed. Each of these protocols provides different benefits and used in different applications [11] The characteristics of the most prevalent communication protocols are shown in Table 2.

Table 2:Most popular communication protocols

Protocols	Main characteristics	Ref
Bluetooth	Bluetooth (IEEE 802.15.1) • Short-range wireless communications. • Cheap. • Communication range of approximately 10m distance. • Speed of 1 Mbps.	[12][6]
ZigBee	ZigBee (IEEE 802.15.4) • Low cost and low power consumption. • Communication range of 10m-20m • Low data rate wireless PAN (250, 40, and 20 Kbps) • Various operating frequencies, (2400, 915, 868) MHz	[13][12]
ZWAVE	• Developed for remote control of residential appliances and light industrial applications. • Maximum data rate is 40kbps • Outdoor communication range of 30m • 128bit AES encryption/ decryption for security issues. • Accommodate for a maximum of 232 devices.	[12][13]
WiFi	Wireless Fidelity (Wi-Fi) IEEE protocol 802.11abg • Most popular Wireless Local Area Network (WLAN) • Speed limited by a network vendor when linked to an access point, to connect to a cloud and internet. • at their broadband speeds (given by the network vendor) • Operating frequency of IEEE802.11b/g is 2.4GHz and IEEE802.11a is 5GHz.	[13][12]
Constrained Application Protocol (COAP)	• Web transfer protocol • Low energy consumption nodes • Utilizes interactive model similar to HTTP client-server	[14]
Message Queue Telemetry (MQTT)	• Light weight protocol placed above TCP/IP. • Low-power consumption • Utilize a quality of service publish and subscribe messaging pattern • 2 bytes Fixed header	[14]
Advanced Message Queuing Protocol (AMQP)	• Operate with message middleware servers and clients in an interoperable manner. • binary protocol with routing, security, and dependability capabilities that facilitates reliable communication.	[14]

C. Middleware Layer

Middleware is a software collection that offers essential services and interface between user applications and operating system. Middleware objectives include reducing programming complexity, managing data, streamlining technical obstacles, abstraction, and hiding a range of intricate technological aspects. User application developers don't have to think about moving software programs between systems, which cuts down on time and effort. Based on the system's role of middleware and the technologies employed, the development cycle is shortened, as well as the job of maintaining and controlling the operating system. [15].

C.1 Data Management

The manufacturing process was optimized by analyzing and providing feedback on real-time production data in the industrial site management. Scientific results were produced in the business operation using big data mining and analysis. The retrieved industrial big data was analyzed and integrated in reference [16]. Finally, automated smart management, smart industrial control, and hierarchical information technology were accomplished.

C.2 Cloud

In an IIoT based manufacturer, the cloud assists the control process. The cloud gives a very reliable alternative for big data applications in the sense that both storage and computing capacity can be upgraded whenever required. Smart gadgets produce a lot of data when they are in operation, which may be sent to the cloud for information systems to analyze. Big data analytics can then assist with system management and optimization, as well as control and supervision [17]. Preprocessing, training, testing, prediction, and model deployment of industrial big data are carried out at this layer due to the cloud's flexibility. Cloud enables resource management and scheduling in accordance with company policies. A distributed data lake is created by the vast quantity of information that is made available on the cloud layer, which makes it possible to use intelligent algorithms to overlay industrial analytics on top of this data lake. Industrial analytics' goal is to uncover hidden links between data at the application layer, allowing decision-makers to make better decisions.

D. Services and Applications Layer

It is the top part of the IIoT systems that provide users with services via mobile applications and the web. It provides real-time visibility into field operations; the applications assist personnel in managing devices, interacting with other systems, and manipulating data. Notifications, alerts, and visualization assist them in making informed and well-informed judgments. Users, like decision-makers and field experts, are given access to the cloud layer's collective knowledge so that sensible decisions may be made. On top of the services and data supplied by the data-analytic layer, this layer is in charge of creating practical and customized applications. It is also in charge of presenting the user with the acquired knowledge in a suitable way. The services and applications layer offers applications and a range of services, such as security, data collecting, data analysis, and visualization.

Users may set up each parameter used in the control algorithm of the smart manufacturer using the Human-Machine Interface (HMI). Additionally, the interface enables authorized users to remotely monitor the controlled and modified factors in real-time from any place at any time [18]. To enable manage and control processes to interact in the event that the database block is changed, the HMI is connected to it. The HMI requests information from the database block when it is needed. The database block then retrieves the information, which the HMI then presents to the user. Figure 4 demonstrates an example of the manufacturer's HMI.

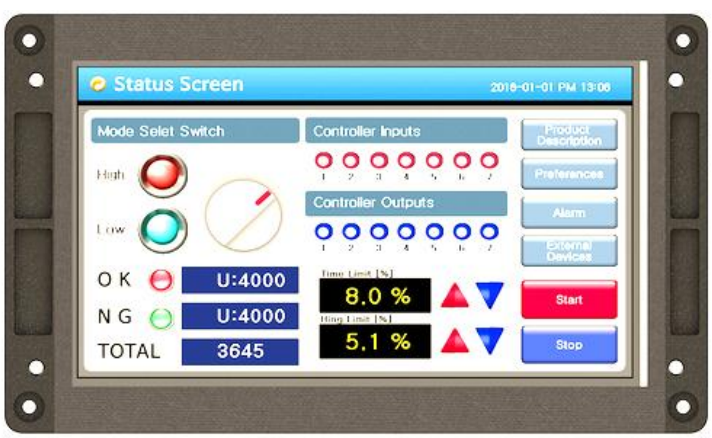

Figure 4:Demonstrate a real human–machine interface

III. Artificial Intelligent in Smart Factory

Artificial intelligence (AI) is a multidisciplinary field, which encapsulates cognition, machine learning, reasoning, learning, decision making, and optimization [19]. It concerns on how to program computers to carry out activities in a smart way that were previously only attainable by people [20], [21]. In addition to its supports, it improves human cognition to make people more productive [22]. Industry 4.0, which encompasses broad domains including automation, optimization, deep learning, machine learning, and digitalization, is fundamentally incomplete without AI algorithms [23]. Analytics methods such as machine learning can be applied to data from IoT devices [5].

Transformation of the manufacturer into smart one by adopting AI into it may include numerous applications but not limited to monitoring environmental signals, smart monitoring, healthcare procedures, failure detection, identification and isolation, optimizing the manufacturer's products, sentiment analyses on customers opinion, decision making, abstraction and context awareness, smart control, and prediction. Environment monitoring covers wide range of indoor and outdoor sensing variables such as temperature, humidity, wind, solar strength, etc. Abstraction and context awareness focuses on extracting useful information about any object like where, when, why and where.

There is a necessity for a large amount of data to implement machine learning algorithms to be used in a number of industrial operations including classification, detection, identification and decision making. Data often has a particular life cycle, which starts by its generation from a source, then collection from the use of suitable sensors. The data is then stored and processed. Finally, data may be visualized, transmitted and/or used in various applications. [24], [25]. The method of collecting and processing data from the physical level is one of the most significant challenges in acquiring industrial data. More data guarantees that maintenance intervals for machines, materials, tools, and products, as well as any other significant parts in the production process, can be predicted with greater accuracy. Though predictive maintenance is costly, it has various advantages such as lowering failure chances, lowering long-term maintenance costs (damage repairs), improving productivity and procedures, etc. Developing alert rules that operators can understand, gathering inconsistent data from sensors that aren't always linked, and collecting vast volumes of monitored parameter data utilizing sensors are a few of the difficulties in modeling machine-learning algorithms for predictive maintenance [26]. Figure 5 illustrates the process of predictive maintenance.

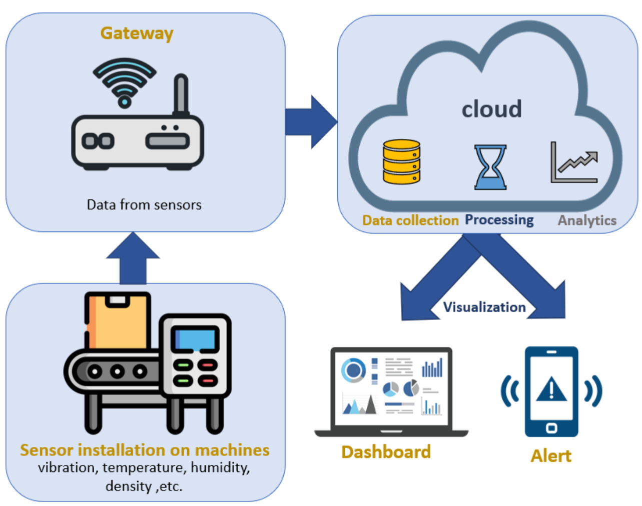

Figure 5:Predictive maintenance process

IV. Industrial Maintenance: Goal and Strategies

The goals and strategies of predictive industrial maintenance in the transformation of a conventional manufacturer into smart manufacturer domain are summarized as follows:

- **Remaining useful lifetime**: This is the prediction of the lifetime or life expectancy of a specific process or event in the system. If a component is about to fail, maintenance will ensure that it is replaced before it fails. It is also feasible to prolong system's life or its components [27].

- **Faulty & anomaly detection**: This parameter identifies instances in the system that are aberrant. If something goes wrong, predictive maintenance will quickly resolve the problem. It also provides for a reduction in the number of deadly accidents [28].
- **Robustness**: Some environments do not provide a convenient location for collecting, monitoring, and analyzing data. One of the goals of predictive maintenance is to be strong enough to work in any environment and adjust when data is scarce.
- **Adaptability**: This goal covers the predictive maintenance system's versatility and ease of development. The goal also includes determining how compact the process is and gaining better control over the production process.
- **Performance**: This criterion describes the system's ability to satisfy demands and respond more quickly. Scalability is also included.
- **Quality**: Because Small and Medium Enterprises (SMEs) compete with larger industries, they rely on their excellent output quality to set themselves apart. As a result, predictive maintenance offered SMEs with high-quality products and data.
- **Cost**: SME's have a limited budget, and predictive maintenance can help reduce an organization's overall costs. Although the installation of predictive maintenance systems is costly, these strategies help to save money in the long run.
- **Adaptability**: This goal encompasses the predictive maintenance system's flexibility and ease of development. The goal also includes determining how compact the process is as well as gaining better control over the manufacturing process.
- **Failure detection**: If a system feature fails, it may be critical to resolve it quickly so that the entire process is not hampered. As a result, several predictive maintenance solutions aim to enhance failure detection because they have been shown to reduce the number of fatal breakdowns.
- **Reliability**: The predictability and stability of the predictive maintenance process are critical. This goal also states that the process should not necessitate the use of extra expert knowledge. It also aids in cost-cutting and downtime reduction.
- **Power consumption**: Many industries seek to be more environmentally friendly and energy efficient in order to reduce their power use.
- **Efficiency**: Because SMEs rely on time, it's critical that the predictive maintenance system be rapid while still being accurate.
- **Scheduling optimization**: Another key goal of predictive maintenance is to keep an efficient schedule for maintenance tasks and to allocate appropriate resources.

V. APPLICATION DOMAINS FOR SMART Manufacturer TRANSFORMATION

The integration of AI and IIoT significantly improves organizational productivity. An IIoT architecture must have scalability, real-time capabilities, data protection, interoperability, and security. The main role of industrial IoT system is performed by intelligent control devices, sensors, and actuators, which gather data and send data to servers. They are further transformed into usable "smart data" at the cloud computing level that utilizes advanced algorithms. By taking into account availability, ability, and location parameters, industrial IoT solutions may assist businesses in determining which field service worker is most suited for the job. The following list summarizes the current major application domains of IIoT and AI to transfer traditional manufacturer into smart one:

A. Industrial Monitoring

IoT can be used in the manufacturing process to track all aspects of production from beginning to end. This thorough process monitoring in real time enables changes to be made in production and operation management to better manage and control the manufacturing process in a timely manner. Additionally, regular monitoring on the manufacturing process helps identify flaws and waste, enabling production managers to minimize waste and unnecessary work [29].
Manoj Kumar and Gouthem [30] proposed water level and quality monitoring system. Sensors are used to continuously monitor the quality of the water including PH, turbidity, temperature, water level indicator, and conductivity. It also transfers water with

contaminants to the filtration system. The IOT system governs the entire setup, and the unit continuously keeps an eye on it. A wireless sensor network for data collecting and intelligent prediction algorithms for maintenance were implemented by Dimitris and John [31] to construct a remote monitoring framework.

B. IoT-Based Remote Control

Through the use of IoT applications, existing network infrastructure may be used to remotely control devices and objects. By doing so, it offers the possibility of more direct real-world interaction with computer systems, which would need less human involvement and lead to higher accuracy, efficiency, and financial benefit.
Karuppusamy [32] outlined a technique for operating industrial machinery that is situated far from the control station. The design uses the Blynk server and the internet media for the particular operations. A monitoring station is kept close to the electrical equipment for the purpose of transmitting the system's status. This concept allows for remote monitoring of any system without the need for physical verification. This improves how well the control devices utilize energy. A technique based on deep learning and IoT was presented by Mahmoud and Minh [33] to regulate the operation of air conditioners in order to lower energy consumption.

C. Predictive Maintenance

Numerous sensor data, including temperature, vibration, humidity, densities, voltages and currents, are included in predictive monitoring maintenance. Algorithms for machine learning can be used to anticipate failure. Every manufacturer aspires to experience the fewest accidents, safety incidents, environmental problems, and malfunctions. Any machine's sensors can monitor its health data points and send out alerts as necessary. However, they cannot predict system faults, types and when it will occur. Instead of only providing data, predictive maintenance aims to develop a system that can estimate probabilities of system failure with high accuracy [34] Tayaba and King Hann [35] developed a predictive maintenance approach for an air booster compressor motor based on recurrent neural networks machine learning model.

D. Supply Chain Management

Supply chain management covers all procedures that covert raw materials into finished commodities. It is the management of the flow of services and goods [36]. Due to globalization, supply chains are no longer as short as they previously were.
They produce enormous amounts of data that, when correctly handled, can yield valuable information since they are enormous. Sorting the supply chain will reveal market circumstances, enabling production to be modified appropriately. By combining numerous IoT communication protocols, Celia and Teresa [37] provided an end-to-end reverse supply chain management system that enables cloud-based inventory tracking of waste electrical and electronic equipment via embedded sensors.

E. Quality Control

Manufacturer’s quality control procedures can be implemented with the aid of AI in the production process. In addition to quickly developing a suitable manufacturing process, expert systems can continually track and automatically regulate changes in the key parameters online, using information transmission and the control model of the AI management system [38]. Stella and Jozef [39] adopted IoT strategy, which allows manufacturers to analyze product data generated by devices in real time and so keep track on the quality of the manufacturing process. Product data can also be utilized to diagnose a product remotely, reducing the time it takes to respond to customer care queries. Ana et. al [40] presented a predictive system to satisfy a variety of goals, including product quality. To construct a decision-support maintenance system, the system used previous data for failure detection. It improved the system's quality by incorporating augmented reality into the human-computer interaction, which improved the efficiency of the required tasks.

VI. CONCLUSION

Smart manufacturing allows factories to transition to highly resilient grid systems. It benefits producers economically by focusing on customer satisfaction while maintaining their competitive advantage. In addition to producing a high-quality product, it increases the production process' efficiency in terms of time, energy, waste management, etc. Additionally, it offers better returns at lesser prices. In this paper, the development of generic hieratical architecture to transform into smart manufacturer based on IIoT technology. Also, Industry 4.0 maintenance goals and strategies are covered. Finally, several industrial researches and applications in the field of IIoT and AI were presented. The paper showed the importance of adopting these two key-enabling technologies for the manufacturer transformation to implement a wide variety of tasks needed as a requirement in Industry 4.0. In addition, the paper list current hot topics and prospective directions that a researcher can explore.

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