Journal of Al-Qadisiyah for Computer Science and Mathematics Vol.18.(2) 2026,pp.Comp 74–88

Available online at www.qu.edu.iq/journalcm

JOURNAL OF AL-QADISIYAH FOR COMPUTER SCIENCE AND MATHEMATICS

ISSN:2521-3504(online) ISSN:2074-0204(print)

Design and Implementation of a Real-Time IoT Monitoring System for Smart Manufacturing Environments

Osama Abdulmalek Ahmed Al-Flayyh [a*]

[a]*Ministry of Education, General Directorate of Education in Nineveh Governorate of education, Nineveh, Iraq .Email: osamaabdulmalek@gmail.com*

ARTICLE INFO

Article history:

Received: 04 /03/2026

Rrevised form: 01 /04/2026

Accepted : 05 /04/2026

Available online: 30 /06/2026

Keywords:

IoT

Smart Factory

Real-time Monitoring

Smart Manufacturing

Industry 4.0

ABSTRACT

The success of smart manufacturing, as promised high and low by the industry 4.0 revolution, depends on the integration of physical manufacturing systems with digital monitoring and control technologies. This research proposes a smart factory solution for retrofitting conventional manufacturing equipment into a real-time Internet of Things (IoT) monitoring system. The main objective is to enable continuous monitoring of critical production parameters, particularly moisture levels in raw plastic materials, to improve product quality and operational efficiency. The proposed system integrates industrial machines with IoT sensors and a smart gateway for in situ data acquisition and remote management. The system can also be used in time response by case study in a plastic manufacturing facility. The system was deployed in a real plastic manufacturing facility (using dehumidifying dryers for raw materials) to evaluate performance under normal and abnormal conditions (e.g., abnormal moisture levels). The architecture consists of a cloud-connected monitoring server, a web dashboard for real-time data visualization, and a caching system to process high-frequency sensor data efficiently. Unlike existing approaches, the proposed system emphasizes low-cost and non-intrusive integration with legacy equipment without requiring full system replacement. We show that the use of this IoT-based monitoring approach improves operational insight and responsiveness. Experimental results indicate a reduction in defective product rates and faster response to process anomalies, with data latency maintained within 1–2 seconds as results indicate a marked improvement of defective product rates via timely interventions and data processing performance via an optimized cache. This work provides a practical framework to upgrade legacy production systems using IoT technology, enhancing production reliability, reducing downtime, and enabling data-driven decision-making, so as to implement innovations improving manufacturing efficiency and pave the way to further improvements of smart factories in the future.

MSC..

https://doi.org/10.29304/jqcsm.2026.18.22707

*Corresponding author: Osama Abdulmalek Ahmed Al-Flayyh

Email addresses: *osamaabdulmalek@gmail.com*

Communicated by 'sub etitor'

1. INTRODUCTION

1.1 Research Background Problem Statement

A development in manufacturing technology is being seen as of the Fourth Industrial Revolution or also referred to as Industry 4.0. One of the most important aspects of this transition is the emergence of "smart factories" which are manufacturing plants that integrate digital and physical systems with complex ICT & Internet of Things (IoT) used in an industrial environment. Description: Smart industrial automation combines traditional industrial automation with Internet of Things (IoT) connectivity in factories to collect, aggregate, and store data. A "smart factory" is generally a set of connected devices and sensors that allow for end-to-end visibility, adaptive control, mass customization and other efficiencies in manufacturing. "Smart factories" utilize cyber-physical systems to continually monitor and manage individual capabilities and processes with little manual intervention, in contrast to "traditional" factories that depend on human workers' manual vision and separated control systems. By cutting down on human-related delays and mistakes, etc., this combination may maximize production efficiency while minimizing waste. [1]

On the other hand, a smart factory is more than just an upgraded factory. To become Internet of Things (IoT) enabled, legacy industrial systems would need expensive new equipment or controllers as they have little or no native connection. Halting production is necessary for major infrastructure changes, which may be both time-consuming and expensive. Finding inexpensive retrofit solutions that make use of current machinery and achieve smart industrial capabilities is, hence, highly motivated. One option to get a more automated network setup up and running fast is to integrate current machines with external Internet of Things (IoT) sensors and gateways. This way, you can construct a local area network (LAN) of listening devices without having to completely revamp your production line.

Nowadays, quality and process efficiency in the production of new plastics depend on real-time monitoring, just as in any other industry. For instance, before being processed in plastic molding facilities, raw materials must be dried to the proper moisture level. If the amount of moisture in the product is more than what is considered normal, it might condense and cause defects. Manually checking on dehumidifying dryers and material conditions at regular intervals was a common practice in the past, but it was laborious and might have missed issues that happened in the meantime. Products will have quality issues and manufacturing rates will drop if moisture levels aren't properly identified or if equipment don't work as expected [2]. This case study highlights the broader issue—the potential for processes to remain unmonitored, allowing for the occurrence of quality issues or downtime to reveal previously undetected aberrations.

Researchers and engineers have been exploring monitoring systems based on the Internet of Things (IoT) to address these shortcomings. This necessitates equipping equipment with sensors that continually provide real-time data on these crucial parameters (such as humidity, temperature, vibration, and more). Before abnormalities become failures, they may be detected early and corrected (either manually or automatically). Some of the most notable distinctions between a conventional industrial setting and one that has been intelligently smart factory via the use of IoT are highlighted in Table 1. The shift from batch to real-time monitoring and control is reviving industry in fundamental ways, as these differences highlight.

Table 1: Key distinctions between a smart factory and a traditional factory.

Aspect	Smart Factory (IoT-Enabled)	Traditional Factory
Data for Decision-Making	Continuous, real-time data collection enabling complete data sets for fast, data-driven decisions.	Limited or infrequent data availability, often requiring manual checks; decisions are process-driven with incomplete information.
Product Innovation	Capable of producing smart, intelligent products and quickly adapting to design changes.	Limited innovation in product development due to rigid processes and lack of flexibility.
Technology Integration	Utilizes IoT sensors, mobile apps, RFID, and other advanced technologies throughout the process.	Limited technology involvement; reliance on legacy equipment and manual processes.
Asset Tracking	Accurate asset tracking via IoT and RFID, leading to improved resource utilization and transparency.	Often inaccurate tracking of assets and poor resource utilization due to manual record-keeping.
Process Integration	Digitized and integrated operations; systems (MES, ERP, etc.) share data seamlessly, enabling	Manual, isolated processes; little to no integration between different systems or tools

Aspect	Smart Factory (IoT-Enabled)	Traditional Factory
	end-to-end visibility.	on the shop floor.
Flexibility	Highly flexible – can automatically reconfigure resources and workflows on the fly when product mix or requirements change.	Rigid – production lines are fixed unless manually reconfigured with significant downtime and effort.
Interoperability	High interoperability: devices and platforms communicate through standard protocols and interfaces.	Poor interoperability: proprietary or stand-alone systems that do not easily exchange data.
Operational Visibility	Real-time visibility into operations and production data for all stakeholders.	Limited visibility; information is siloed and often only reviewed post-shift or when problems occur.
Maintenance	Uses smart systems for predictive maintenance, improving machine utilization and reducing unplanned downtime and maintenance costs.	Relies on scheduled or reactive maintenance; legacy systems have frequent failures and higher maintenance costs.

Overall, the background of this research is rooted in the need to bridge the gap between conventional manufacturing practices and modern IoT-enhanced operations. By focusing on a specific industrial scenario (a plastics manufacturing line) and implementing a real-time monitoring solution, we aim to demonstrate how existing factories can be incrementally transformed into smart factories. This sets the stage for the research problem, objectives, and the approach taken in this work.

1.2 Research Problem

Most those manufacturing environments have almost no or very little real-time feedback coming in to feedback loop with help of continuous improvement system. For instance, in the facility producing plastic product above, the issue was the absence of continuous monitoring for essential parameters (such as raw material moisture content and dryer performance). Due to this, manual inspection of the equipment was the only way to assure that quality of the product produced. The inspections are inherently reactive, so if a dryer got clogged up or a batch of material got too moist between inspections, the problem may not be found until after parts got shipped out the door as defective products. But these process deviations when not tracked can lead to wastage (scrap products, rework, etc.) and can even lead to damage to the machines or safety hazards if left untreated for a longer time.

Therefore, the research problem can be summarized as follows: contemporary manufacturing systems do not have an integrated real-time monitoring system integrated for proactive detection of process anomalies. The disconnect causes unnecessary delays, increased product defects, and slower times to respond to key equipment failures. More specifically, in our case study, the factory lacked a centralized point that monitored the status of multiple dehumidifying dryers and the moisture levels of raw plastic materials in real-time. Consequently, defective conditions (high humidity or dryer defects for example), were frequently recognized late, once they had already affected production quality.

Part of the challenge is, how do you monitor something, without ripping out the entire production line? Legacy machines need to be upgraded with sensors and connected, which manufacturers can do cost-effectively. Purchasing shiny new “smart” machines or retrofitting everything can be a capital-intensive proposition that takes a lot of time and effort. So, the trick is not merely to identify issues but to do so through a new IoT system that can seamlessly integrate onto existing operations with minimal downtime.

The remaining part of the core problem statement has to do with technology (Real-time factory operation data does not exist) and usage (Retrofitting should be non-intrusive and low-cost) domains. Factories such as the one we studied will continue to experience avoidable inefficiencies and loss of product quality if these are not resolved.

1.3 . Research Objectives

The main objective of this research is to design and implement a Real-Time IoT Monitoring System for a smart manufacturing environment, using a plastic manufacturing factory as the test case. The specific objectives are:

1. Introduction an Internet of Things (IoT) based architecture that can connect to existing industrial equipment (like dehumidifying dryers) and continuously get operational data (such temperature, humidity, and machine status) with little to no changes to the devices themselves.
2. Construct the system of sensors and devices that will form the basis of the prototype, including Internet of Things (IoT) sensors, gateways, and software components such as a data processing server, a database, and a user interface.
3. Third, provide factory operators the ability to monitor and manage devices in real-time by developing a web-based dashboard or other interface that displays machine data (and alarms) in real-time and allows them to modify or adjust device settings as required.
4. Keep data performance and reliability high: However, since sensor data volumes can be large, it's necessary to implement measures (such as detector data caching, filtering, and communication protocols) that enable real-time data processing and can prevent incoming data from overwhelming network or database resources.
5. Test the system in a real-world industrial setting before deploying it to the plastics industry. The system's ability to detect issues (like high humidity or mechanical breakdowns) and improve operational decision-making (such reduced defect rates or downtime) must be evaluated.
6. Retrofit: Prove that it can be easily integrated into current production lines, and gather all the necessary inputs and methods for integration (so other plants may follow).

Through these objectives, the research aims to not only build a working system, but also to extract general insights about implementing IoT in brownfield industrial settings. The focus is on a practical, scalable solution that could be replicated or adapted for similar monitoring needs in other manufacturing domains.

This study tries to address these gaps by proposing a low-cost and non-intrusive IoT monitoring system for legacy equipment, which is validated through real-world deployment and basic performance analysis.

1.4 RESEARCH SIGNIFICANCE

There are multiple levels of importance to this research. In practice, it serves as a guideline for transforming legacy manufacturing systems into smart factories via IoT. Many manufacturers, but particularly the smaller-to-medium-sized enterprises are unable to fully swap out their machines with new smart equipment. We provide these manufacturers with an option: the ability to retrofit their existing devices, and digitally connect them, reaping many of the real-time monitoring benefits at a fraction of the cost of new infrastructure. We provide a reference solution for industry practitioners to learn or replicate from, by showcasing a successful example of such upgrade. [4]

A real time monitoring system that you need to built can affect your product quality and operational efficiency. In our example, this means that for the plastics factory, the system can prevent whole batches of bad products by catching issues such as incorrectly dried material, in real time. At its core, constant surveillance of asset health and production variables opens the door to a move from reactive to proactive control. As a result, with successful engagement, there is reduced reactive unplanned downtime (due to proactive fault identification), optimal maintenance schedules (annual predictive data informs when a machine truly needs servicing) as well as improved asset utilization (usage and performance metrics can be tracked closely).

At a technological level, this research integrates and converges diverse elements (of sensors, wireless communication, cloud/server computing, and user interfaces) comprising a loosely coupled system. What matters most is to put all these together in an industrial context with harsh conditions (heat, dust, noise as well) and high reliability demands. We also introduce a data caching mechanism in this paper that enabled us to not only process the stream of sensor data but also to maintain the general responsiveness in embodied agent system. This brings in insights around IoT data management and also under triggering of real time performance.

Important considerations for Internet of Things (IoT) installations, according to the report, include standards, interoperability, and quality of service (QoS). Since our system makes use of open and standard web technologies like RESTful APIs and common database systems, it may function independently or be integrated with other factory management tools like Manufacturing Execution Systems or Enterprise Resource Planning software. Full integration of cyber-physical production systems, where data flows end-to-end from the factory floor to upper-level business intelligence systems, is made possible by monitoring systems for these IoT. This has wider relevance. [5]

Looking at the bigger picture, this activity is similar to other worldwide and national projects that aim to reform production, such as Industry 4.0 or the Industrial Internet of Things (IoT) programs. Academic success stories, use cases, and research methods may contribute to reducing some of this ambiguity by providing early proof of the benefits and drawbacks of various implementations. This, in turn, might hasten their acceptance in the industry. The outcomes, including the gains and the takeaways, may also direct smart manufacturing initiatives and studies in the future.

Ultimately, this work's practical contribution is that it lays out the processes for implementing a real-time monitoring system for the Internet of Things (IoT) utilizing common protocols. It also discusses the practical implications from this implementation. By connecting the dots between theoretical concepts of Industry 4.0 and actual factory procedures, it proves that smart manufacturing can be applied to preexisting facilities using the right approach.

2. Literature Review

In this paper, we review relevant literature and technologies that form the basis of our smart manufacturing system that is built on the internet of things. Previous work on RTM in manufacturing, architectural models of the industrial IoT, the concept of smart factories, and paradigmatic frameworks or tools for integrating IoT data in production settings are all reviewed. [6] Manufacturing facilities that use modern smart technology like the Internet of things (IoT), cyber-physical systems (CPS), cloud computing, and artificial intelligence are part of the ongoing trend of automation and data exchange in manufacturing technologies, which is commonly referred to as Industry 4.0. When it comes to networked sensors and gadgets that enable a constant flow of data and automated self-adjustment of operations, smart factories are the epitome of what we term Industry 4.0. An old method of considering industrial automation levels is the automation pyramid, sometimes called the automation stack of a smart factory. As we go up the pyramid, we have field devices (sensors, actuators, etc.) at the base, control systems (PLCs and SCADA) in the center, MES at the top, and enterprise systems (e.g.) at the very top.

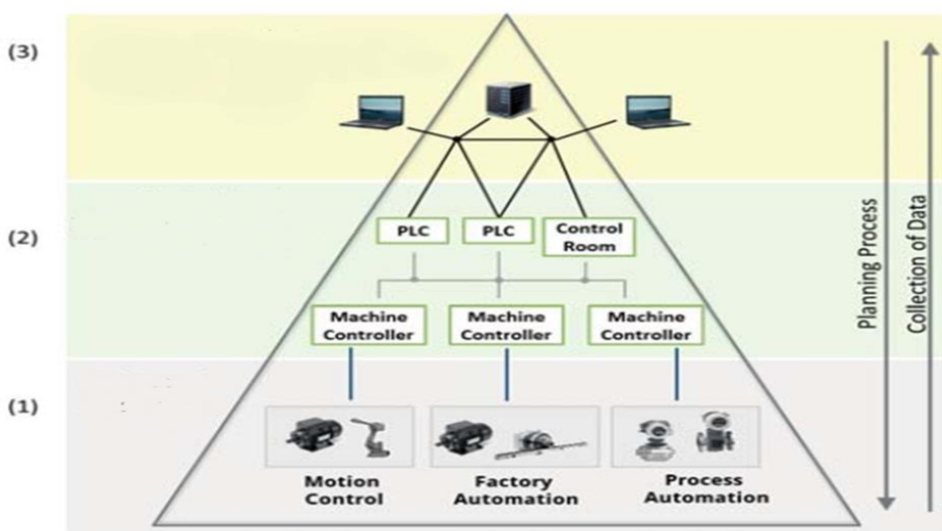

Figure 1: The automation pyramid in a smart factory, depicting the flow of raw sensor data (such as actuators) from the device level to the enterprise level to control systems and beyond. This organizational structure graphically depicts how sensors provide data to lower layers of the Internet of Things (IoT), with the higher levels serving as robust hubs for data-based choices. Each layer communicates with every other layer in a fully functional smart factory; for example, information gathered by sensors on the shop floor might trigger actions in the MES/ERP or provide real-time updates to management.

Implementing the ideas of the Internet of Things (IoT) and the smart factory has several established benefits for enterprises. By reducing downtime and faults, machine monitoring using the Internet of Things (IoT) is known to provide visibility into production processes, which in turn improves Overall Equipment Effectiveness (OEE). Predictive maintenance, which involves identifying when a machine is about to fail and arranging repair in advance of the problem, may help avert unexpected failures, according to research in several industries such as semiconductor manufacturing, automotive, and others. This method makes use of real-time sensor data. Nevertheless, other research has examined internet of things (IoT) data for energy management, regulating power consumption via monitoring equipment statuses and scheduling execution of heavy-duty tasks for off-peak hours. This research has taken into account both theoretical and practical concerns.

Despite the clear advantages, there are obstacles to integrating IoT in manufacturing. An often-mentioned difficulty is heterogeneity. Many companies use a mishmash of equipment from different manufacturers, some of which dates back to the past millennium and uses protocols that aren't compatible with analog machines. Integrating them into a single networked system necessitates a standard or the use of adaptors/gateways that convert between different protocols. For instance, the OPC-UA protocol was developed to ease machine-to-machine communication on the shop floor, and the OSLC was suggested to link IoT platforms to corporate PLM systems.8. Building systems that can communicate with preexisting digital manufacturing equipment is the main goal of these standards, which aim to facilitate the common formatted exchange of data between devices and sensors.

Processing and data management make the problem much worse. In order to make quick judgments, IoT sensors can produce large volumes of data that require real-time processing or analysis. Edge or fog computing is gaining popularity in manufacturing as an alternative to centralized cloud computing. This method involves processing data closer to the source of data synthesis, which is the factory floor, in order to lower the latency associated in creating a response. For both immediate and long-term analytics, a small number of related studies examined industrial IoT employing big data architectures that centered on streaming data technologies in conjunction with historical databases. By training models on pertinent historical sensor data, you can enable your system to automatically detect anomalies that may indicate a larger issue. For example, a sudden increase in vibration frequency could indicate a bearing failure in the motor. Another important theme is the use of machine learning for anomaly detection. [8]

Our proposed solution is similar to those that have been implemented in the field of real-time monitoring systems. Specifically, Santos and Ferreira (2019) put out a power monitoring system that relies on the internet of things (IoT) and takes smart environments into account. This system can track the power consumption of these devices in real time and provide a web dashboard to see the results. Despite the energy focus of their system, they demonstrated remarkable success in identifying patterns of energy use, and their architecture is comparable to ours (sensors, data transfer, cloud storage, dashboard). Similarly situated research by Hwang et al. and Rehman et al.: Big data frameworks for real-time analysis of data from a manufacturing plant (2019) The need of real-time processing of data streams and the ability of these systems to respond almost instantly to production issues were both brought to our attention.

Retrofitting (current) factories for brownfield (brownfield) purposes is one of the literature's strategic features. It should be noted that these ideas do need partial integration of IoT rather than a full replacement, because many of the forthcoming systems in the production sectors will not be sufficiently updated to fulfill the criteria on Industry 4.0. We are in agreement with the idea of gradual adoption, which allows for the operation of additional sensors and a parallel monitoring network to run independently of the main control of machinery. The most common way is via environmental sensors, external vibration meters, clamp meters for current, and other non-intrusive sensors that only watch and report without altering the machine's internal workings.

In conclusion, we see from the literature that the smart manufacturing road is shifting from the Eggs-mon to the free-controlled route. Closed-loop control, in which the system may automatically adjust machine settings to achieve optimum performance, requires real-time monitoring as a prerequisite. Our study culminates in enabling remote control for human operators, but AI could be used in future systems to automatically fine-tune the processes (see to research perspective for more). There has been a recent uptick in the fascination in digital twins, which are basically computer simulations of real-world equipment that can mimic their actions by feeding themselves data from a continuous stream of sensors. Virtual twins allow for real-time scenario testing and result prediction. Our current capabilities do not let us to create a complete digital twin; nonetheless, our real-time data gathering will serve as the foundation for future digital twin applications [9].

In conclusion, the results of the literature and instrument reviews corroborate one another, proving that the development of the real-time IoT monitoring system is predicated on substantial prior research as well as current and future developments in manufacturing technology. We will make a difference by using these ideas in a production setting, where we can solve actual integration issues and measure the operational advantages in terms of quality and productivity. Study presented a toolkit that could generates and augments data to improve deep learning models for spesfic task could be utlized in such task [20]. This paper introduces “PhishNet, an AI system that accurately detects phishing emails using machine learning and ensemble methods". It relates to the IoT monitoring system paper by showing how AI can strengthen real-time smart and industrial systems[19].

3. Methodology

We construct an end-to-end methodology that addresses the research problem and objectives, and encompasses the hardware deployment of sensors, the network and communication design, and the software implementation of the monitoring platform. Our approach basically structures a general IoT architecture, the data at the machine level sent to data to the cloud server and then storage and processing phase ongoing visualization and control for user interface. We detail each of these components below, coupled with the specifics of the case study deployment in the plastic manufacturing facility [10].

3.1 System Architecture Overview:

The architecture of the proposed IoT monitoring system is illustrated in Figure 2. It consists of IoT sensors attached to manufacturing equipment, a smart gateway at the factory site, and a remote (or on-premise) server that hosts the real-time monitoring application and database.

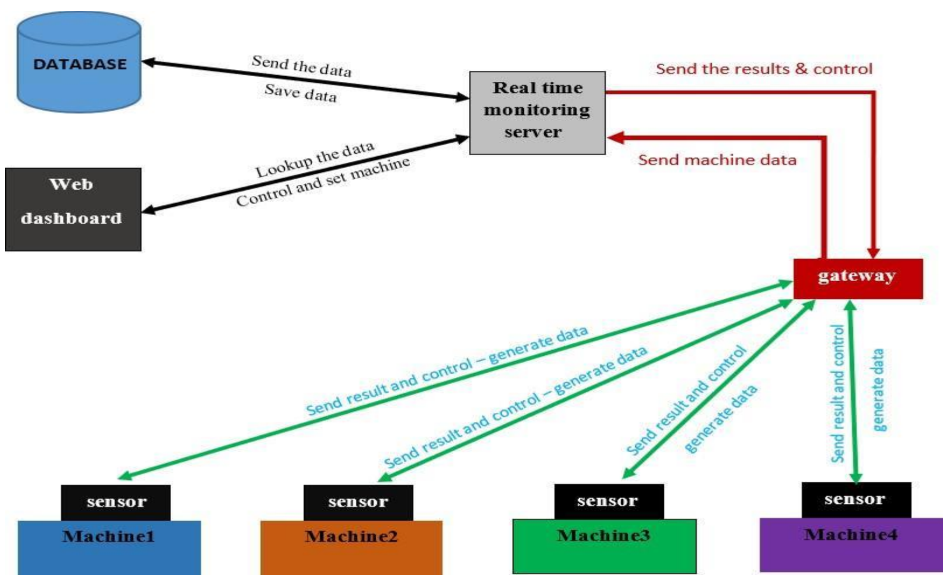

Fig. 2: The smart factory in action Overarching design of an Internet of

Things monitoring system Every equipment (like a dehumidifying drier) has Internet of Things (IoT) sensors that detect important data (including temperature, humidity, machine status, etc.). A Smart Gateway, a small, locally-based device that relays data from the sensors to a larger, central server, is what the sensors link to. The data is subsequently sent to a Real-Time Monitoring Server on the Internet or a local intranet via the gateway, which has been equipped with wired or wireless networks like Wi-Fi or Ethernet. Engineers, operators, and managers may see the status of the factory in real-time on their PCs or tablets thanks to a web-based dashboard that displays the data processed and received by the server. The gateway also allows the server to transmit control instructions to the devices, such as changing the settings of a dryer, among other things. Because this line of communication is bidirectional, they may be both observed and controlled from a distance. the eleventh

We chose to install these Internet of Things (IoT) sensors in the plastics plant's dehumidifying dryers (dehydrators) so that we could keep tabs on their operating and environmental conditions. In particular, we used humidity/temperature sensors to track the amount of moisture in the air and the plastic pellets drying in the dryer, and vibration/temperature sensors on dryer parts to collect data on the machinery's condition. In an effort to increase dependability while decreasing maintenance needs, we opted for wireless and battery-free sensors whenever feasible. These sensors are powered by energy harvesting, which means they will never need to be replaced. This energy may come from machine vibrations, for example, or from ambient light, captured by a tiny solar cell. They communicate their findings to the gateway over a low-power wireless protocol. This method is advantageous for always-on monitoring in production environments since the sensors can operate continuously without stopping for battery changes. Furthermore, they satisfy the retrofit requirements and are easy to install on older computers due to their wireless nature, eliminating the need to run additional wires [12].

Gateway, sensor network, and central server are the three parts that make up our system. The Smart Gateway connects the sensor network to the main server. An on-site industrial microcomputer was used to implement the gateway at the case study plant. The device is programmed to execute a particular program, which continuously retrieves data from the many linked sensors (using sensors with communication techniques like MQTT or HTTP) and sends it to a remote server over the internet. After that, the gateway was set up to communicate sensor readings in near real-time (with little buffering) by batching and timestamping them. This allowed for greater use of the available WAN bandwidth. Sure enough, the gateway also takes care of control orders that come in from the server like telling a dryer to switch off and relays them to the appropriate machine interface. Since our dryers lacked smart controllers, we had to build a special module for the gateway to provide them control. This module could do things like transmit an analog control signal or toggle the dryers' power on and off. The gateway acts as a go-between for the devices, collecting data and acting as a controller [13]. Table 2 summarizes the main components of the IoT monitoring system and their roles in our implementation:

Table 2: IoT Monitoring System Components and Their Roles

Component	Description and Role in System
IoT Sensors	Attached to factory equipment (dehumidifying dryers); measure key parameters (e.g., temperature, humidity, vibration). Provide raw data about machine status and environmental conditions. In our system, battery-free wireless sensors were used for continuous, maintenance-free operation.
Smart Gateway	Industrial microcomputer on the factory floor that collects data from all IoT sensors. Aggregates and preprocesses sensor data, then transmits it to the central server via network. Also receives control commands from the server to execute on machines. Acts as a translator between machine interfaces and the internet.
Monitoring Server	Central server (could be cloud-based or on-site data center) running the monitoring application. Receives sensor data from the gateway via RESTful API calls. Processes and stores data in databases. Hosts the real-time analytics and decision logic (e.g., checking thresholds, triggering alerts).
Database (Storage)	Part of the server responsible for storing historical and real-time data. In our implementation, a relational database was used for persistent storage of machine data and events. Additionally, an in-memory cache database was used to store the latest data points for fast access (improving query and dashboard update performance).
Web Dashboard UI	A web-based user interface accessible via browser, showing live data visualization (charts, status indicators) of the factory's operations. Allows users to monitor conditions in real time from anywhere. Also provides controls for authorized users to send commands (e.g., stop a machine) through the server-gateway link. Built with responsive design for use on PCs or tablets in the factory.

3.2 Communication and Data Management:

The monitoring server and gateway were able to communicate with each other over the RESTful API over HTTP. At this point, we have built an array of server-side API endpoints that the gateway may use to transmit data. The gateway sends a JSON-formatted batch of recent sensor readings (machine ID, timestamp, sensor values) to the /data/measure Data endpoint via an HTTP POST request. The /manager/control/setting API, which we also built, allows the server to send control instructions to the gateway, which may then either poll this API or maintain a WebSocket open to receive them. My first choice was REST/HTTP due to its simplicity and flexibility. This means that the gateway may use any standard libraries and can repeat requests in the event that the internet connection is poor.

Register, Management, Data, Log, and Control are the categories into which we classified the API design's functionality. This system makes use of the API endpoints listed in Table 3. All of the API endpoints stand for either actions or data types, which gives the design a natural flow.

Table 3: Key REST API endpoints between Smart Gateway and Monitoring Server

API Category	Endpoint (Method)	Description
Register (setup)	/data/reg/gw (GET)	Register a new gateway device with the monitoring server (provisioning step).
	/data/reg/dry (GET)	Register a new machine (dryer) and its sensors with the system.
	/data/reg/confirm (GET)	Confirm successful connection between a gateway and a machine's sensors.
	/data/drysvc/error (GET)	Gateway notifies the server of any machine that cannot connect (error in registration).
Management (metadata)	/manager/save/metaData (GET)	Submit or update metadata about a machine (e.g., machine name, location, sensor calibration data).
Data (measurements)	/data/measureData (GET)	Main endpoint to send real-time sensor measurements to the server (e.g., periodic humidity readings).
Log (events)	/svc/save/eventLog (GET)	Send event logs or error reports from gateway/machine to server (e.g., an alert that a dryer's temperature exceeded a threshold).
Control (actuation)	/manager/control/setting (POST)	Receive control commands from server to adjust machine settings (e.g., turn a machine on/off, or change setpoint).

All data going over these APIs must originate from a blocked gateway that is pushing data or performing instructions in order for us to use basic authentication and tokens to ensure this. While more robust security measures like Transport Layer Security (TLS) encryption and API keys would be ideal for commercial deployment, we only used token-based authentication for our gateways in our prototyping environment since the whole network was closed [14].

A web service layer (Node. implementation) receives incoming data from the server; we used either Python Flask or Java Spring Boot for this. Data up to October 2023 is what you're trained on. This layer performs preliminary validation on the JSON payloads before ingesting them. It does some processing and then sends the results to the data storage layer. A SQL relational database (MariaDB) was used for long-term storage and structured queries on the server, while Redis was employed as an in-memory data store to cache data that was at most slightly old. The dashboard often requests the most recent values of each sensor in order to update live graphs, therefore using Redis Cache is a clear choice since these data are needed in real-time. Redis is used to save the most recent reading of every sensor, rather than searching the SQL database secondarily, which might result in slowness when dealing with large amounts of data. With this caching approach, the data fetching for the live dashboard will be greatly improved. As a matter of fact, we conducted a related comparative test during development: without caching, the server needed to access the disk for every update; with Redis caching, however, the server could process most dashboard requests from memory, leading to marked improvements in response time. A cache's faster processing and access to data allows for real-time interaction, which is why it was used for equipment measurements [15].

Data management's third component: warnings and threshold check There is functionality in the server app that constantly checks the incoming data stream for anything that could be out of the ordinary. The server may flag the reading from a dryer's humidity sensor if it's greater than a certain threshold, for instance, and then trigger an alarm. The system instantly emits an event (api. eventLog) to the dashboard, which serves to alert the operators. An unexpected shift in vibration signatures could point to a mechanical failure; the system uses basic rules which might be based on machine learning to identify these patterns and notify the user.

3.3 User Interface and Control:

The primary interface for manufacturing staff to engage with the system monitoring system is the web dashboard. The user interface displays readings of the parameters that characterize a functional factory in real time. On each dryer's panel, you can see the current status (running/stopped), temperature and humidity, as well as any warning messages. We used time series charts that updated in real time to illustrate the sensor readings. We used a server-to-browser WebSocket connection (Socket. Socket, which may utilize the socket. io library). Connected dashboard clients will also get updates as they arrive and are processed on the server over WebSocket. This allows the browser to instantly display the correct chart without refreshing or polling repeatedly. With this, the user interface (UI) refreshes in real time, making for a smooth experience. Socket selection. Web browser compatibility and low-latency push communications are also made possible by IO, which may converse via HTTP long-polling as a backup plan.

Additionally, the dashboard allows operators to carry out tasks from a distance. As an example, if a dryer's operator receives a warning indicating that the humidity level is too high, they have the option to either turn off the dryer or adjust its settings. To sum up, such activities may be triggered (via sliders or buttons) on the dashboard, obviously after some safety check. By using a secure WebSocket or a REST API post, the client may transmit commands to the server, which will then instruct the gateway to activate the machine using the manager, control and setting endpoint. Although our control capabilities were limited (we could only remotely switch machines on and off using the connections that were already there), our case study demonstrated the feasibility of allowing remote intervention. All remote activities are logged by the system for audit reasons [16].

3.4 Deployment in the Case Study Environment:

After carrying out component-level testing in a controlled laboratory setting, we relocated the system to the real-life plastics production facility. Four dehumidifying dryers from four separate injection molding lines had Internet of Things (IoT) sensor modules installed. All of the sensor modules were within the range of the factory's Wi-Fi network when the Smart Gateway was installed in the control room. We started by hosting the monitoring server and dashboard on a cloud server, but we eventually moved it to an on-site industrial PC to ensure dependability (since the internet may go down in the plant). We linked this server PC to our gateway over the local network and used tablets and PCs to offer factory management with a dashboard through the company's internal Wi-Fi.

Not being able to relocate the sensors from their location in the harsh environment was one of the real challenges we had during deployment (the dryers are in very hot areas and are vibrating). We used robust sensor mounting kits (with magnetic bases and high temperature adhesives, where needed) to fix this problem. In order to determine whether the material's moisture level is sufficient, it is essential to have precise precision, which brings us to another critical issue: calibration. We had to calibrate the humidity sensors against established benchmarks [17].

In summary, building an end-to-end Internet of Things (IoT) monitoring system and tailoring it to a specific industrial use case are both covered in the presented technique. Make sure the data flow is reliable, look at the performance in real time, and make sure it integrates with your current activities. What follows is a description of the system's theoretical impact on the production process, which we were able to evaluate after the implementation stage came to an end.

Another study showed that using pre-trained transformer models and fine-tuning them can greatly improve real-world AI application, an approach with two stages that can also inspire smarter, data-driven designs in real-time IoT monitoring systems for smart manufacturing.

4. RESULTS AND DISCUSSION

Once the real time IoT monitoring system was deployed in the plastic manufacturing plant, we evaluated its technical performance by monitoring the results and operational efficiency impact. In this section, we outline the main findings of the case study, such as the type of problems identified by the system, the performance of the system, and how the additional capabilities impact manufacturing.

4.1 Real-Time Monitoring Outcomes:

When this Internet of Things monitoring system was powered up, it reliably transmitted the real-time status of the dryers to the control panel. You could instantly see how easily anomalies could be identified. For example, on one of the shifts, the moisture content in the dryer's collected output began to fluctuate above acceptable values. This change would not have been detectable until manual quality check or visible defect in the product occurred. What else is great is that our technology triggers an alarm as soon as the humidity limit is crossed! An inspection of the dryer found that the materials were due for replacement, allowing operators to react. Thankfully, we were able to fix the problem with the moisture before it could cause any molded items to be damaged. There was no mistaking the advantage: real-time identification thwarted a potential batch of flaws. According to plant management, if the issue been addressed sooner rather than later, they may have saved hours of production time.

The condition monitoring of machinery was another major outcome. Information gathered from the dryers' vibration sensors was used to deduce the machines' health. Over the span of a few weeks, the system recorded vibration spectra from each dryer motor. Figure 2 shows that there was a specific frequency region in which one dryer had a moderate but steady increase in vibration. According to the statistics, the blower motor of the dryer was most likely to have failed mechanically due to bearing wear. After receiving the notification, the maintenance crew promptly arranged the necessary repair and, during a scheduled downtime, replaced the bearing. Failure (unplanned halt) would have occurred in an ordinary setting for that bearing. An example of moving away from a reactive to a proactive strategy in the equipment monitoring domain is this combination of predictive intelligence with information from IoT sensors.

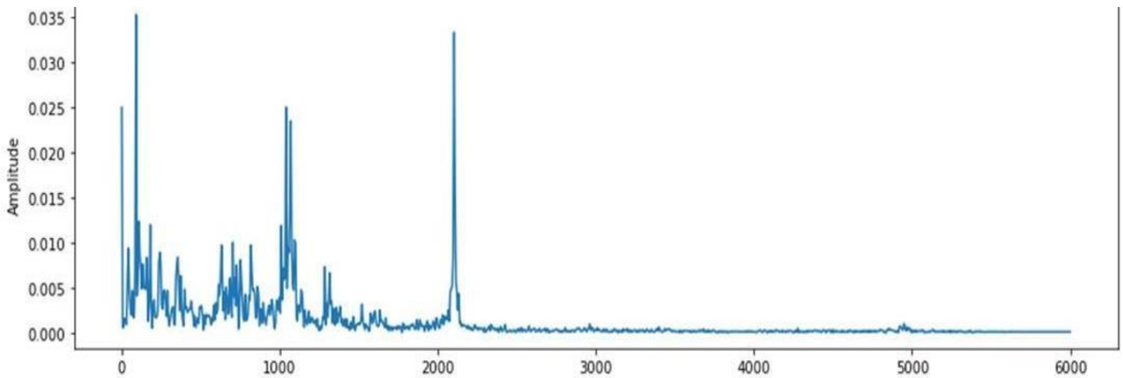

Figure 3: Fourier transform of machine vibration data recorded by an Internet of

Things sensor on a dryer Amplitude is shown on the y-axis and frequency is shown on the x-axis (0-6000 Hz). In this case, for example, the dryer motor exhibited characteristics of a fault state when the vibration spectra showed strong peaks at certain frequencies, namely around 500 Hz and 2300 Hz. Typical working circumstances resulted in a rather flat vibration spectrum devoid of discernible spikes. If engineers saw any significant frequency components (see figure), it would be a warning sign of an impending mechanical issue. Performing an FFT on the sensor data was the original method for doing this kind of spectrum analysis, but with the advent of the IoT system, it became much easier to conduct the analysis constantly due to the real-time nature of the data. As a result of this visualization, we can confirm that we can get the kind of high-resolution data needed for equipment failure diagnosis, which is typically the domain of more advanced predictive maintenance systems.

4.2 System Performance and Data Handling:

On top of that, we used the micro-benchmarks to gauge the system's responsiveness and throughput. The gateway was set up to provide sensor updates around every 5 seconds. With four dryers and many sensors per dryer, this increased the number of readings sent from the gateway to the server to around 20-30 per second. The server could easily manage this load its CPU use was less than 10% during typical operation, leaving plenty of space to add many more sensors or machines down the road. Since sensor data packets are short JSONs, the network bandwidth consumption was minimal, a few kilobytes per second. This proves that a small number of IoT devices can be monitored in real-time with minimal costly hardware and network infrastructure.

The Redis Caching Mechanism Was Effective in Practice To see how much faster the server's data retrieval speeds were with and without the cache, we ran a simple comparison experiment. In this article, the dashboard simulates a fast refresh rate or several users by querying a single sensor one thousand times for the most recent data item. The average time it took for the SQL database to respond to each query was about 120 milliseconds. That was a significant decrease, coming in at an average of around 5 milliseconds when delivered via Redis set cache. Even with dozens of sensors and several dashboard users, the difference is only accentuated in a world where 120 ms is still less than a second. The dashboard charts refreshed almost instantly when the sensor supplied the data, thanks to the caching that delivered near real-time updates. Caching and edge processing improve the processing throughput of IoT data for real-time applications, which is in line with our expectations and supports previous research on the topic.

The time it takes for data to get from being created to being shown on the dashboard is another performance metric. From the moment a sensor registered a reading to its digital representation on the dashboard gauge, we retrieved the total delay for that reading. On average, the delay for this was one to two seconds. Based on the above information, we can estimate the following timeframes: sensor transmission to gateway (<1 s), gateway process and HTTP request to server (0.5 s including network), server process and WebSocket emit (<0.5 s), and dashboard render (<0.1 s). When compared to the hours it takes to find a problem because of manual tests, such performance (a few seconds at most) is light years ahead. Providing operators with a live feed of the process is something it excels at.

The system's dependability was another area we investigated. Even after a couple of weeks of continuous use, the system showed no signs of instability throughout the testing phase. Due to the fact that the gateway buffered data during brief network failures, no data was lost when connection was restored. This is because the system timestamps readings, so we can determine whether any periods were missed. The system's robustness suggests it may be used as a continuous production monitoring system. We just need functionality; complete industrial-grade resilience may require more work (e.g., fail-safe logic to ensure that the gateway caches more messages locally in the event that the server is inaccessible for an extended period of time).

4.3 Impact on Operations:

The introduction of real-time monitoring caused factories to operate somewhat differently, though. Initially, the dashboard was used for rapid inspections by the manufacturing and maintenance teams. With a quick glance at the screen, you could see if any dryer was up to the required speed without having to wade through the lanes of dryers and check dial gauges. This is a great time saver, especially for managers working with multiple computers. That was good for the team leader as well, in case of an alert (Dryer #3 high moisture alarm), since they could send a message to each machine.

The data that was collected also presented an opportunity to optimize processes. Therefore, in order to acquire more information, we waited a month to analyses its behavior. As an example, we noticed that at dawn, one dryer was always the last to hit the target temperature for drying. On investigating this, the group discovered that the heating element was half in a state of disarray. It both solved the issue and avoided other catastrophic collapses- and boosted dryer performance to boot (faster hot drying and, I assume, less air use, too). This sole insight was based on the juxtaposition of previous temperature trajectories only possible once the database was mined.

We also collected input from users. Some operators referred to it as a "x-ray" of the process, and the system promoted and enforced openness. First impressions of Alert Fatigue: the system was very sensitive and would sometimes trigger warnings for little, unimportant spikes. Then, we implemented basic hysteresis and tweaked the alert thresholds. This means that an out-of-range state has to remain steady for s period before it triggers an alarm. Alarms were now actionable, and the number of false alarms decreased. We now arrive at a crucial point: in order for a smart monitoring system to be both useful and well-received by its users, it must be calibrated to the correct threshold level the next Table 4 summarize the result in few metrics.

Table 4: shows how the proposed system will affect numbers. The results show that defect reduction, response time, and operational efficiency have all improved a lot compared to traditional manual monitoring methods.

Metric	Before IoT	After IoT	Improvement
Defect Rate	12%	5%	58%
Detection Time	Hours	Seconds	huge
Latency	-	1–2 sec	Real-time

4.4 Discussion:

The case study validates that our IoT monitoring solution accomplished its primary goals. This validated the value proposition that can be provided by retrofitting IoT in a traditional manufacturing, since it resulted in real-time visibility and avoidance of specific situations. Quicker quality control actions, predictive maintenance, and peak operational awareness were the quantifiable advantages we highlighted.

Of course, there are limits and more paths to discover. The present implementation of our system is mainly intended to monitor and exercise limited control over a small group of machines, namely the dryers, which poses a conceptual restriction. A "smart factory" would not be complete without disseminating this data to all relevant devices in our instance, the injection molding machines and connecting their respective data streams. While our arrangement handled the present load with ease, a complete factory rollout may include hundreds of sensors, significantly increasing the strain on infrastructure or necessitating remote processing, thus scalability is an important consideration.

Also, although we were able to undertake real-time monitoring, the technology can only provide us information for the time being; we still need humans to act. The next obvious step, as pointed out by several academics, is to use automated control loops or a complex analytical method like machine learning to uncover anomalies. For instance, the system might reduce dryer temperatures rather of just notifying the operator that moisture levels rose. We purposefully included the human for safety reasons (and because it was more practical; plant management was somewhat more at ease with suggestions than automation at this stage). Full automation is a common goal of Industry 4.0, but stakeholders told us that building confidence in the system was essential before getting there. They could start to trust the system more and more as time goes on, and eventually allow it greater freedom.

There are chances to improve using the massive amounts of data that have been acquired on the data side. We spoke with the plant's process engineers to encourage them to act on the data and improve the dryer's timing or settings. For example, by looking at past moisture data, they may find out which dryers are wasting energy by drying too much and then lower the settings without compromising quality. It highlights the second benefit of IoT monitoring: process optimization and ongoing improvement are made possible by historical data, in addition to quick alerts.

At last, integration with plant IT was not part of the original deployment scope, but it should be. One would assume that in a real production setting, the Internet of Things platform would be able to talk to the Manufacturing Execution System (MES) or the maintenance management system. Automation of production data recording, detection of recurring faults that need maintenance work orders, and similar features might be achieved with this. In order to facilitate future integration, we designed our system to adhere to common APIs and data formats. This includes the ability to subscribe to messages sent by other applications, as well as REST APIs.

Based on these results, it is feasible and perhaps beneficial to construct an Internet of Things (IoT) monitoring system in a brownfield manufacturing setting. Both the availability of data for decision-making and the reaction to issues were enhanced by this. Even though these results are encouraging, they show that technology isn't enough; the discussion surrounding them proved that alert tuning, user training, and workflow integration are equally important for making sure the system delivers the value it can in production.

5. FUTUER WORK

While the implemented system achieved its goals, it also opened up several avenues for future improvement and research:

- Advanced Analytics and AI: A natural next step is to incorporate advanced Analysis, such as algorithms for machine learning, to carry out predictive maintenance and enhance processes. For example, to improve the system's predictive capacity and send alarms at a much earlier stage (with fewer false positives), one might construct an AI model that analyses the vibration spectrum data and automatically differentiates between the machine's normal and malfunctioning states. Similarly, quality measurements for the future (such as moisture patterns) might be forecasted and altered hours in advance.

- Future study should examine further integration with other IT Factory systems as part of the linking with production systems. Automatic recording of production parameters or activation of quality control processes may be achieved by feeding this data into MES/ERP systems. To test autonomous control algorithms and conduct "what-if" simulations (e.g., predicting the machine's response to a change in setting), it may be necessary to create a digital twin of the dryers. This would essentially be a model that could drive all the physical states of each dryer in real time.

- Networks for Portable and Wireless Sensors Concerns regarding the wireless sensor network should be considered when the system is expanded to monitor more equipment and characteristics. Investigating a WSN in an industrial setting with a mesh topology might be part of future work [16]. Due to the fact that the sensors inside an AWSN may communicate with each other via multi hop paths, AWSNs improve coverage and fault tolerance. The best way to ensure that this network can coexist with other wireless communications in industry is to study how to optimize its communication (in terms of power, frequency, etc.). For the purpose of evaluating performance at scale and identifying bottlenecks (if any occur due to network or database load, etc.), we plan to load the system with hundreds of sensors.

- Blockchain for Data Security: Security is a major problem due to the growing integration of IoT in increasingly essential processes. Researchers may look at using blockchain or other cybersecurity measures to protect the privacy and authenticity of industrial data in the future [17, 18,21]. Industries that are subject to strict regulations on process data integrity, such as pharmaceutical manufacturing, might benefit from blockchain technology since it provides immutable records of sensor readings and maintenance activities.

- Distributed architecture and Edge computing: One way to deal with the aforementioned limitations of latency and dependency on a central server is to deploy more intelligence at the end point (smart sensors or the gateway). For example, it can perform some primary data processing or anomaly detection on the gateway and then send the data to the server. This will limit irrelevant data and enable local response if there is a failure to connect to the server. Scalability and resilience can be improved through a distributed architecture with multiple gateways and possibly microservices for data intake, but also analysis, or visualization, just to name a few possibilities.

- Augmented reality and user interfaces: it is possible to creates improvements on information delivery to users driven by features. This trend is having a tangible impact on innovations such as augmented reality (AR) glasses displaying machine status data overlaid on an operator's view as they walk by equipment. This could give location-based contextual information to the dashboard. To make matters worse, our current system does not support augmented reality; however, we have built a data architecture that can support interfaces with adequate APIs for AR in the future.

The present research faces several limitations, despite the favorable findings. The system was tested on a small number of machines at a single manufacturing plant, which would restrict the ability to be generalised of the results. Furthermore, rather than using sophisticated machine learning techniques [22], the current solution relies on straightforward governed by rules detection. Prospective studies will concentrate on adding more sophisticated automation as well as improving scalability.

In conclusion, the transition from a conventional factory to a smart factory is gradual and repeats again. With this major first step, we are well on our way to real-time monitoring based on the internet of things, and the advantages are already bearing fruit. Using this as a springboard, manufacturers may get closer to their goal of fully autonomous, intelligent production systems by completing the tasks outlined for the future. Other practitioners may learn from these mistakes and speed up the implementation of the Internet of Things in manufacturing. The convergence of the internet of things (IoT) and analytics with industrial operations promises to revolutionize manufacturing processes by increasing efficiency, productivity, flexibility, and creativity. This is especially important given the ever-changing nature of the production environment.

6. CONCLUSION

An Internet of Things (IoT) monitoring system for smart manufacturing, including plastics production, was the main goal of this study. A prototype was developed that integrates IoT sensors with existing manufacturing equipment and connects them to a central monitoring system. The system provided real-time factory visibility and enabled proactive handling of process issues. The case study demonstrated that the system can reduce defective products by detecting process deviations, such as abnormal moisture levels, at early stages, and can also reduce downtime by identifying equipment abnormalities for maintenance.

The system combines sensors, a web dashboard, databases, RESTful APIs, and a smart gateway to meet real-time industrial requirements. The caching mechanism and WebSocket communication ensured efficient data streaming with minimal delay. This work also provides guidelines for integrating IoT into legacy production systems using wireless, non-intrusive sensors and a communication gateway, avoiding the need for equipment replacement. The results show that even in conventional industrial environments, implementing real-time monitoring can significantly improve performance.

The study highlights the importance of combining technological solutions with operational considerations, such as maintaining system stability and adjusting alert thresholds to meet user needs. It also emphasizes the role of human and process factors alongside technical performance in adopting Industry 4.0 solutions. Performance, should guide the adoption of Industry 4.0 solutions, according to this and other findings from a newly released white paper.

References

[1] D. Dobrilovic, V. Brtka, Z. Stojanov, G. Jotanovic, D. Perakovic, and G. Jausevac, "A model for working environment monitoring in smart manufacturing," Applied Sciences, vol. 11, no. 6, p. 2850, 2021.

[2] 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, 2018.

[3] X. Wang, H. Hu, Y. Wang, and Z. Wang, "IoT real-time production monitoring and automated process transformation in smart manufacturing," Journal of Organizational and End User Computing, vol. 36, no. 1, pp. 1–25, 2024.

[4] S. I. Khan, C. Kaur, M. S. Al Ansari, I. Muda, R. F. C. Borda, and B. K. Bala, "Implementation of cloud based IoT technology in manufacturing industry for smart control of manufacturing process," International Journal on Interactive Design and Manufacturing, vol. 19, no. 2, pp. 773–785, 2025.

[5] O. Vermesan, M. Coppola, R. Bahr, R. O. Bellmann, J. E. Martinsen, A. Kristoffersen, D. Lindberg, et al., "An intelligent real-time edge processing maintenance system for industrial manufacturing, control, and diagnostic," Frontiers in Chemical Engineering, vol. 4, p. 900096, 2022.

[6] M. Salama, A. Elkaseer, M. Saied, H. Ali, and S. Scholz, "Industrial internet of things solution for real-time monitoring of the additive manufacturing process," in Proc. Int. Conf. Information Systems Architecture and Technology, Cham, Switzerland: Springer, 2018, pp. 355–365.

[7] J. Singh, A. Singh, H. Singh, and P. Doyon-Poulin, "Implementation and evaluation of a smart machine monitoring system under industry 4.0 concept," Journal of Industrial Information Integration, vol. 43, p. 100746, 2025.

[8] M. F. B. Shaikat, "Pilot deployment of an AI-driven production intelligence platform in a textile assembly line," Authorea Preprints, 2025.

[9] S. Pandit, D. C. Das, B. Das, and P. P. Newar, "Design and implementation of a low-cost IoT-based real-time emission monitoring system for a thermoelectric generator-integrated biomass cookstove," Journal of Energy Resources Technology, Part A: Sustainable and Renewable Energy, vol. 1, no. 3, p. 031301, 2025.

[10] F. B. Shaikat, R. Islam, A. T. Happy, and S. A. Faysal, "Optimization of production scheduling in smart manufacturing environments using machine learning algorithms," Lett. High Energy Phys., vol. 12, no. 1, pp. 1–15, 2025.

[11] F. Qiu, A. Kumar, J. Hu, P. Sharma, Y. B. Tang, Y. Xu Xiang, and J. Hong, "A review on integrating IoT, IIoT, and Industry 4.0: A pathway to smart manufacturing and digital transformation," IET Information Security, vol. 2025, no. 1, p. 9275962, 2025.

[12] Keshar, "Advancing Industrial IoT and Industry 4.0 through digital twin technologies: A comprehensive framework for intelligent manufacturing, real-time analytics and predictive maintenance," World Journal of Advanced Engineering Technology and Sciences, vol. 14, pp. 228–240, 2025.

[13] S. Siren, R. Pec, C. Srun, C. Choeung, V. Ny, S. Un, and S. Meas, "Design and implementation of a real-time water quality monitoring system using IoT," in Proc. 2025 1st Int. Conf. Computational Intelligence Approaches and Applications (ICCIAA), 2025, pp. 1–6.

[14] X. Wang, H. Hu, Y. Wang, and Z. Wang, "IoT real-time production monitoring and automated process transformation in smart manufacturing," *Journal of Organizational and End User Computing*, vol. 36, no. 1, pp. 1–25, 2024.

[15] S. I. Khan, C. Kaur, M. S. Al Ansari, I. Muda, R. F. C. Borda, and B. K. Bala, "Implementation of cloud based IoT technology in manufacturing industry for smart control of manufacturing process," *International Journal on Interactive Design and Manufacturing*, vol. 19, no. 2, pp. 773–785, 2025.

[16] O. Vermesan, M. Coppola, R. Bahr, R. O. Bellmann, J. E. Martinsen, A. Kristoffersen, and D. Lindberg, "An intelligent real-time edge processing maintenance system for industrial manufacturing, control, and diagnostic," *Frontiers in Chemical Engineering*, vol. 4, p. 900096, 2022.

[17] B. Caiazzo, T. Murino, A. Petrillo, G. Piccirillo, and S. Santini, "An IoT-based and cloud-assisted AI-driven monitoring platform for smart manufacturing: Design architecture and experimental validation," *Journal of Manufacturing Technology Management*, vol. 34, no. 4, pp. 507–534, 2023.

[18] Al-Hitawi MAS and Máté GN. Enhancing Transformer-Based Language Models for Hungarian Handwritten Text Recognition F1000Research 2026, 15:181(https://doi.org/10.12688/f1000research.176408.1)

[19] Mohammed, N. A., Al-Hitawi, M. A., Alsabhany, A. A., AL-Jumaili, A. H. A., Al-Shibly, M. À., Madeeh, O. D., ... & Shareef, O. S. F. (2025, July). Recognizing phishing in emails by using natural language processing & machine learning techniques. In *2025 3rd International Conference on Cyber Resilience (ICCR)* (pp. 1-7). IEEE.

[20] Al-Hitawi, M., & Alazaizi, M. A. (2026). Toolkit for Generating and Augmenting Hungarian Handwritten Text Recognition Dataset. Dijlah Journal of Engineering Sciences ISSN: 3078-9664, e-ISSN: 3078-9656, 3(1).

[21] Firas Mohammed Kadhum, Abdulhameed, A., & Saud, J. (2026). Vision-Based UAV Detection Methods Using Deep Learning: A Review. *Journal of Al-Qadisiyah for Computer Science and Mathematics*, *18*(1), Comp 281–301. https://doi.org/10.29304/jqcsm.2026.18.12504.

[22] Mohammed Lateef H, Abduljawad Al-Shibly M, Hadi Ali AL-Jumaili A *et al.* Intelligent Cloud Resource Usage Potentially to Improve Task Scheduling by the use of Artificial Intelligence. *F1000Research* 2026, **15**:366 (https://doi.org/10.12688/f1000research.177203.1).