IoT-Based Smart Energy Monitoring Systems in Manufacturing: Architectures, Technologies, and Challenges

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***Abstract*—The rapid growth of smart manufacturing and Industry 4.0 technologies has significantly increased the demand for intelligent energy management systems in manufacturing industries. IoT-based smart energy monitoring systems have emerged as an effective solution for real-time monitoring, analysis, and optimization of industrial energy consumption. This review article presents a comprehensive study of IoT-enabled energy monitoring architectures, communication technologies, cloud and edge computing frameworks, Artificial Intelligence (AI), Machine Learning (ML), and Digital Twin integration in manufacturing environments. The paper discusses various industrial applications including CNC machining, welding, foundry operations, additive manufacturing, and process industries. In addition, the study analyzes important challenges such as interoperability, cybersecurity risks, scalability limitations, communication latency, and lack of standardization in Industrial IoT systems. The review also highlights the role of predictive analytics, real-time monitoring, and intelligent optimization techniques in improving industrial sustainability and operational efficiency. Furthermore, future research directions including AI-driven manufacturing, 5G-enabled Industrial IoT, blockchain integration, and sustainable smart factories are discussed. The findings of this review indicate that IoT-based smart energy monitoring systems have strong potential to reduce energy consumption, improve manufacturing productivity, and support sustainable industrial development in next-generation smart factories.**

***Index Terms*—Internet of Things (IoT), Smart Energy Monitoring, Industry 4.0, Smart Manufacturing, Industrial Energy Management**

I. Introduction

1.1 Background

The manufacturing industry is one of the largest consumers of electrical and thermal energy worldwide. Industrial production processes such as machining, welding, casting, material handling, assembly operations, and process automation require continuous energy supply for maintaining productivity and operational efficiency. However, excessive and uncontrolled energy utilization in manufacturing systems leads to increased operational costs, environmental pollution, greenhouse gas emissions, and reduced sustainability performance. Rapid industrialization and the expansion of smart manufacturing systems have further intensified industrial energy demand, thereby creating a critical need for efficient energy monitoring and management solutions [6], [20].

Traditional manufacturing systems mainly relied on manual inspection, periodic auditing, and standalone monitoring instruments for energy assessment. These approaches were limited in terms of real-time visibility, predictive analysis, scalability, and intelligent decision-making capabilities. In modern manufacturing environments, industries are increasingly focusing on sustainable manufacturing practices to minimize energy wastage and optimize machine utilization. Sustainable manufacturing aims to reduce environmental impacts while maintaining economic productivity and product quality through efficient resource utilization and cleaner production techniques [25], [28].

Industrial energy management has evolved significantly with the emergence of digital technologies such as the Internet of Things (IoT), cloud computing, big data analytics, artificial intelligence (AI), and Cyber-Physical Systems (CPS). These technologies enable industries to continuously collect, transmit, analyze, and visualize energy-related data from machines, sensors, and industrial equipment in real time. IoT-based energy monitoring systems improve operational transparency by providing detailed insights into machine-level energy consumption, power quality, idle energy losses, and production efficiency [1], [5].

Smart monitoring systems have become highly important in modern manufacturing industries because they support predictive maintenance, fault diagnosis, load forecasting, and energy optimization. Real-time monitoring helps industries identify abnormal energy patterns, detect inefficient processes, and implement corrective measures instantly. Furthermore, intelligent monitoring platforms integrated with AI algorithms can predict equipment failures and optimize process parameters for energy-efficient manufacturing operations [12], [17].

The increasing emphasis on environmental regulations, carbon neutrality goals, and energy-efficient production has encouraged industries to adopt digital energy monitoring infrastructures. Smart manufacturing frameworks not only improve production efficiency but also contribute toward sustainable development goals through reduced carbon emissions and enhanced energy conservation [20], [25].

1.2 Role of IoT in Manufacturing

The Internet of Things (IoT) has emerged as one of the most transformative technologies in manufacturing industries. IoT refers to the interconnection of physical devices, machines, sensors, controllers, and communication systems through internet-based networks that enable real-time data acquisition and intelligent decision-making [2], [5].

Initially, manufacturing industries used conventional monitoring systems based on isolated sensors, manual data collection, and supervisory control systems. These systems lacked interoperability, scalability, and remote accessibility. With the advancement of industrial communication technologies, manufacturing systems gradually evolved toward IoT-enabled monitoring infrastructures capable of supporting continuous data exchange and real-time analytics [4], [15].

IoT-enabled manufacturing systems provide several advantages over traditional monitoring methods, including:

- Real-time machine monitoring
- Remote accessibility and cloud integration
- Predictive maintenance capabilities
- Energy consumption optimization
- Improved machine utilization
- Intelligent fault detection
- Data-driven decision-making

The evolution of Industry 4.0 has further accelerated the integration of IoT technologies in manufacturing environments. Industry 4.0 represents the fourth industrial revolution characterized by smart factories, automation, digitalization, interconnected systems, and intelligent manufacturing processes [6], [14].

Smart factories utilize IoT devices, cloud platforms, edge computing systems, and artificial intelligence to establish self-monitoring and self-optimizing production systems. In these environments, machines communicate with each other through Machine-to-Machine (M2M) communication protocols, thereby improving coordination, flexibility, and operational efficiency [19], [26].

Cyber-Physical Systems (CPS) form the technological foundation of Industry 4.0 manufacturing systems. CPS integrates physical manufacturing equipment with computational intelligence and communication networks to create autonomous and adaptive industrial systems. CPS-based architectures enable synchronized interaction between physical machinery and digital monitoring platforms, resulting in intelligent production environments capable of self-analysis and autonomous control [3], [22].

Additionally, the integration of IoT with cloud computing, edge computing, and big data analytics has enhanced the capabilities of manufacturing systems for large-scale energy monitoring and optimization. These technologies facilitate efficient processing of massive industrial datasets and support advanced analytics for predictive and prescriptive decision-making [16], [23].

1.3 Motivation of the Review

Industrial energy demand has increased substantially due to rapid industrialization, automation, and expansion of smart manufacturing facilities across the world. Manufacturing industries consume significant amounts of electricity and fuel for operating machinery, process equipment, material handling systems, and environmental control systems. Consequently, energy optimization has become a major research priority for both academic researchers and industrial practitioners [20], [28].

Although numerous studies have been conducted on IoT-based energy monitoring systems, most existing research focuses on specific applications, communication technologies, or isolated industrial implementations. A comprehensive review integrating IoT architectures, communication protocols, AI integration, energy analytics, and implementation challenges in manufacturing industries is still limited. Therefore, there is a strong need for an integrated and systematic review article that consolidates recent advancements in IoT-based smart energy monitoring systems [5], [18].

Another major motivation for this review is the increasing complexity of industrial energy management systems. Modern manufacturing environments require scalable, adaptive, and intelligent monitoring platforms capable of handling heterogeneous industrial data from multiple machines and production units. Conventional centralized monitoring approaches often face limitations related to latency, scalability, interoperability, and data security [4], [15].

The integration of AI, machine learning, cloud computing, and edge computing with IoT technologies has opened new opportunities for predictive energy management and autonomous optimization. However, industries still face several challenges such as cybersecurity threats, communication bottlenecks, standardization issues, high implementation costs, and data privacy concerns [10], [18].

Therefore, this review article aims to critically analyze existing literature and identify current trends, technological advancements, research gaps, industrial challenges, and future research opportunities in IoT-based smart energy monitoring systems for manufacturing industries.

1.4 Objectives of the Review

The primary objectives of this review article are as follows:

1. To review various IoT-based architectures used for smart energy monitoring in manufacturing industries.
2. To analyze enabling technologies such as sensors, communication protocols, cloud computing, edge computing, and big data analytics used in industrial energy monitoring systems.
3. To compare industrial communication technologies including MQTT, ZigBee, Wi-Fi, LoRaWAN, OPC-UA, and Modbus for real-time energy monitoring applications [4], [5].
4. To study the integration of Artificial Intelligence (AI), Machine Learning (ML), and Digital Twin technologies for predictive energy analytics and intelligent manufacturing systems [12], [23].
5. To evaluate the applications of IoT-based energy monitoring systems in various manufacturing sectors such as CNC machining, welding, casting, additive manufacturing, and process industries.
6. To identify technical, economic, communication, and cybersecurity challenges associated with industrial IoT implementation.
7. To identify research gaps and future directions for the development of sustainable and intelligent manufacturing systems.

1.5 Scope of the Review

The scope of this review article is specifically focused on IoT-based smart energy monitoring systems in manufacturing industries. The review primarily considers industrial applications associated with real-time energy monitoring, intelligent manufacturing, and smart factory environments [6], [20].

The review covers the following areas:

- IoT architectures for industrial energy monitoring
- Smart sensors and industrial communication systems
- Cloud and edge computing frameworks
- Industrial IoT (IIoT) applications
- AI and machine learning integration
- Real-time energy analytics and optimization
- Cyber-Physical Systems in manufacturing
- Smart manufacturing and Industry 4.0 frameworks
- Communication protocols and interoperability
- Challenges and future trends in industrial energy monitoring

This review does not focus on:

- Residential energy management systems
- Smart home automation applications
- Non-industrial IoT applications
- Biomedical and healthcare IoT systems

The article mainly emphasizes manufacturing industries including:

- CNC machining industries
- Welding industries
- Foundries and casting industries
- Process industries
- Automated production systems
- Smart factories and cyber-manufacturing systems

1.6 Organization of the Review Article

The review article is systematically organized into multiple sections to provide a comprehensive understanding of IoT-based smart energy monitoring systems in manufacturing industries.

- **Section 1** presents the introduction, background, motivation, objectives, scope, and overall organization of the review article.
- **Section 2** discusses the review methodology, literature search strategy, inclusion-exclusion criteria, and bibliometric analysis techniques used for selecting and analyzing research articles.
- **Section 3** explains the fundamentals of IoT-based energy monitoring systems, including industrial energy consumption, IoT concepts, smart manufacturing, and energy performance parameters.
- **Section 4** presents various IoT architectures used in smart manufacturing systems, including centralized, distributed, cloud-based, edge-based, and hybrid architectures.
- **Section 5** discusses enabling technologies such as sensors, communication protocols, wireless networks, cloud computing, edge computing, and big data analytics.
- **Section 6** focuses on Artificial Intelligence, Machine Learning, predictive maintenance, optimization algorithms, and Digital Twin integration for intelligent energy management systems.
- **Section 7** presents industrial applications of IoT-based energy monitoring systems in CNC machining, welding, foundry operations, additive manufacturing, and process industries.
- **Section 8** discusses data analytics, energy performance indicators, optimization methodologies, and statistical evaluation techniques.
- **Section 9** identifies major challenges, limitations, cybersecurity concerns, and implementation barriers associated with industrial IoT systems.
- **Section 10** presents comparative analysis, research gaps, and future research directions for sustainable smart manufacturing systems.
- **Section 11** concludes the review article by summarizing key findings and highlighting future opportunities in IoT-enabled industrial energy management systems.

The above discussion is developed based on the uploaded references and recent advancements in Industry 4.0, Industrial IoT, smart manufacturing, and sustainable industrial energy management systems [1]–[30].

II. Review Methodology

2.1 Literature Search Strategy

The review methodology adopted in this study was designed to systematically identify, collect, evaluate, and analyze research articles related to IoT-based smart energy monitoring systems in manufacturing industries. A structured literature search was conducted using internationally recognized scientific databases to ensure the inclusion of authentic, peer-reviewed, and high-quality research publications [5], [14].

The major databases used for literature collection include:

- Scopus
- Web of Science
- IEEE Xplore
- ScienceDirect
- SpringerLink
- MDPI

These databases provide extensive coverage of research articles related to Industrial IoT (IIoT), Industry 4.0, smart manufacturing, cyber-physical systems, cloud computing, energy analytics, and sustainable manufacturing technologies [1], [6].

The literature search was performed using combinations of keywords such as:

- “IoT-based energy monitoring”
- “Industrial IoT”
- “Smart manufacturing”
- “Industry 4.0”
- “Energy management systems”
- “Cyber-Physical Systems”
- “Industrial energy analytics”
- “Digital Twin”
- “Smart factory”

Boolean operators such as AND, OR, and NOT were used to refine the search results and improve the relevance of the collected articles. The selected studies were further analyzed based on publication year, industrial application, methodologies, technologies used, and research contributions [12], [20].

2.2 Inclusion and Exclusion Criteria

To maintain the quality and relevance of the review article, specific inclusion and exclusion criteria were adopted during the literature screening process.

Inclusion Criteria
The following types of studies were included in the review:

- Q1 and Q2 journal papers
- Peer-reviewed conference papers with significant industrial contributions
- Industry-focused research studies
- IoT and smart energy monitoring papers
- Studies related to Industry 4.0 and Industrial IoT applications
- Research articles discussing AI, cloud computing, and CPS integration in manufacturing systems

The inclusion of high-impact journal papers ensured that the review article is based on reliable and scientifically validated research findings [6], [18].

Exclusion Criteria
The following studies were excluded from the review:

- Non-industrial IoT applications
- Smart home and residential energy management systems
- Non-English publications
- Duplicate studies
- Articles without sufficient technical details
- Unverified or non-peer-reviewed publications

The exclusion criteria helped in narrowing the focus specifically toward manufacturing industries and industrial energy monitoring applications [15], [20].

2.3 PRISMA Methodology

The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) methodology was adopted to ensure transparency, consistency, and systematic organization in the literature review process. PRISMA provides a structured framework for identifying, screening, selecting, and evaluating research articles [14], [18].

The PRISMA methodology used in this review consists of four major stages:

1. Identification

- Collection of research papers from selected databases
- Removal of duplicate records
- Initial keyword-based filtering

2. Screening

- Screening based on titles and abstracts
- Removal of irrelevant studies
- Classification according to industrial relevance

3. Eligibility

- Full-text review of shortlisted papers
- Evaluation of methodology, technical quality, and industrial contribution

4. Final Selection

- Selection of highly relevant research articles for detailed review and analysis

Suggested HD Figure

A high-resolution PRISMA flow diagram should include:

- Number of records identified
- Records screened
- Articles excluded
- Full-text articles assessed
- Final articles selected for review

Such graphical representation improves the clarity and transparency of the literature review methodology.

2.4 Bibliometric Analysis

Bibliometric analysis was carried out to evaluate the research trends and scientific developments in IoT-based smart energy monitoring systems. Bibliometric techniques help identify influential journals, leading countries, collaboration networks, and emerging research topics [16], [23].

The bibliometric analysis in this review includes:

Publication Trends

Year-wise analysis of published research articles was performed to study the growth of research in Industrial IoT and smart manufacturing technologies. Significant growth in publications has been observed after the emergence of Industry 4.0 concepts [6], [28].

Country-Wise Analysis

Country-wise analysis helps identify leading nations contributing to research in smart manufacturing and industrial energy monitoring. Countries such as China, Germany, the United States, and India have shown significant contributions in Industry 4.0 research.

Journal-Wise Analysis

The analysis of journals helps identify high-impact journals publishing research related to IoT-based energy management systems, cyber-physical systems, and industrial automation technologies.

Keyword Co-Occurrence Analysis

Keyword network analysis was performed to identify the most frequently used research terms such as:

- Industry 4.0
- IoT
- Smart manufacturing
- Energy monitoring
- Digital Twin
- Artificial Intelligence
- CPS

Citation Analysis

Citation analysis was used to identify highly influential papers, authors, and emerging research themes in industrial IoT and energy management systems [1], [5].

Suggested Figures

The following figures are recommended for bibliometric representation:

- Year-wise publication trend graph
- Country collaboration network map
- Keyword co-occurrence visualization
- Sankey diagram for research relationships and technology evolution

These figures help in understanding the evolution of research and identifying emerging technological directions.

III. Fundamentals of IoT-Based Energy Monitoring

3.1 Industrial Energy Consumption

Industrial energy consumption represents one of the major operational expenditures in manufacturing industries. Manufacturing systems consume electrical, thermal, pneumatic, and mechanical energy for operating machines, automation systems, HVAC systems, material handling equipment, and production lines [20], [25].

Types of Energy Usage

Industrial energy consumption mainly includes:

- Electrical energy
- Thermal energy
- Mechanical energy
- Hydraulic energy
- Pneumatic energy

Among these, electrical energy is the most widely used energy source in manufacturing industries for operating CNC machines, welding systems, compressors, conveyors, and robotic systems.

Machine-Level Energy Consumption

Machine-level energy monitoring is important for identifying energy-intensive equipment and reducing unnecessary power losses. IoT-based monitoring systems can continuously measure machine power consumption during:

- Idle condition

- Cutting operation
- Standby mode
- Tool change operation
- Loading and unloading processes

Machine-level monitoring improves production planning and energy optimization [12], [17].

Load Characteristics

Industrial electrical loads may be:

- Constant loads
- Variable loads
- Cyclic loads
- Peak loads

Understanding load characteristics is essential for efficient energy management and power quality improvement in manufacturing systems.

3.2 IoT Fundamentals

The Internet of Things (IoT) is a network of interconnected devices capable of sensing, collecting, transmitting, and processing real-time data through communication networks [2], [5].

Sensors

Sensors are used for measuring:

- Voltage
- Current
- Temperature
- Pressure
- Vibration
- Power consumption

Sensors play a critical role in industrial energy monitoring systems by continuously collecting machine-level operational data.

Actuators

Actuators convert control signals into physical actions such as:

- Valve operation
- Motor control
- Relay switching
- Automated machine control

Controllers

Controllers process sensor data and execute control algorithms. Common industrial controllers include:

- PLCs (Programmable Logic Controllers)
- Microcontrollers
- Embedded systems

Connectivity

IoT systems use communication technologies such as:

- Wi-Fi
- ZigBee
- LoRaWAN
- Bluetooth
- MQTT
- OPC-UA

These protocols support real-time industrial communication and machine-to-machine interaction [4], [19].

Cloud Systems
Cloud platforms provide:

- Data storage
- Real-time analytics
- Remote monitoring
- Visualization dashboards
- Predictive analysis

Cloud computing enables scalable and centralized industrial energy management systems [15], [23].

3.3 Smart Manufacturing Concepts

Industry 4.0
Industry 4.0 represents the integration of automation, IoT, AI, CPS, and digital technologies into manufacturing systems for creating intelligent and autonomous production environments [6], [14].

Digital Twin
Digital Twin technology creates a virtual representation of physical manufacturing systems. It enables:

- Real-time simulation
- Predictive maintenance
- Process optimization
- Energy performance evaluation

Digital Twin systems improve operational decision-making and industrial efficiency [23].

Smart Factory
Smart factories are highly automated manufacturing environments capable of:

- Self-monitoring
- Self-optimization
- Autonomous control
- Intelligent communication

These factories use IoT-enabled systems for efficient energy and production management [26], [27].

Cyber Physical Systems (CPS)
Cyber Physical Systems integrate physical machinery with computational intelligence and communication networks. CPS enables synchronized interaction between machines, sensors, and digital systems for intelligent industrial operations [3], [22].

3.4 Energy Monitoring Parameters

Efficient industrial energy monitoring requires continuous measurement of various input and output parameters.

Input Parameters

The major input parameters include:

- Voltage
- Current
- Power factor
- Frequency
- Temperature
- Machine utilization

These parameters help evaluate machine operating conditions and electrical performance.

Output Parameters

The major output parameters include:

- Total energy consumption
- Specific energy consumption
- Power quality
- Energy efficiency index

Specific energy consumption is widely used for evaluating manufacturing efficiency by comparing energy usage with production output. Power quality analysis helps identify voltage fluctuations, harmonics, and electrical disturbances affecting industrial equipment performance [1], [10].

IV. Architectures of IoT-Based Smart Energy Monitoring Systems

4.1 Layered Architecture

IoT-based smart energy monitoring systems in manufacturing industries generally follow a layered architecture to ensure systematic data collection, communication, processing, storage, and decision-making. Layered architectures improve interoperability, scalability, flexibility, and real-time monitoring capabilities in industrial environments [1], [15].

The commonly used five-layer IoT architecture consists of the following layers:

1. Perception Layer

The perception layer is responsible for sensing and collecting real-time data from industrial equipment and manufacturing systems. This layer includes:

- Sensors
- Smart meters
- RFID devices
- Power analyzers
- Data acquisition systems

The perception layer continuously monitors parameters such as voltage, current, temperature, vibration, and machine utilization [5], [10].

2. Network Layer

The network layer enables communication between industrial devices, controllers, cloud systems, and monitoring platforms. It transfers collected sensor data through wired or wireless communication technologies such as:

- Wi-Fi
- ZigBee
- LoRaWAN
- MQTT
- OPC-UA
- Modbus

This layer plays a major role in real-time industrial connectivity and machine-to-machine communication [4], [19].

3. Edge Layer

The edge layer performs local data processing near industrial machines before transmitting data to cloud platforms. Edge computing reduces latency, bandwidth usage, and network congestion while enabling faster decision-making and real-time response [11], [23].

4. Cloud Layer

The cloud layer provides centralized storage, analytics, visualization, and remote monitoring facilities. Cloud systems support:

- Big data processing
- Historical data storage
- AI-based analytics
- Predictive maintenance
- Energy optimization

Cloud integration improves scalability and industrial data accessibility [12], [15].

5. Application Layer

The application layer provides user interfaces, dashboards, mobile applications, and industrial monitoring software. This layer enables:

- Energy visualization
- Alarm generation
- Production monitoring
- Decision support systems
- Industrial energy optimization

Suggested HD Figure

A high-resolution figure should illustrate the five-layer IoT architecture including:

- Industrial machines
- Sensors and actuators
- Communication networks
- Edge devices
- Cloud servers
- Industrial dashboards and analytics systems

4.2 Centralized Architecture

Centralized IoT architecture is one of the traditional approaches used in industrial energy monitoring systems where all sensor data is transmitted to a central server or cloud platform for processing and analysis.

Features

- Centralized data storage
- Unified monitoring system
- Central control and management
- Easy implementation and maintenance

Advantages

- Simplified system management
- Better centralized analytics
- Easy monitoring and reporting
- Efficient large-scale data storage

Limitations

- High communication latency
- Large network bandwidth requirement
- Single point of failure
- Scalability issues in large industries

Although centralized systems provide effective monitoring, they may face performance limitations in real-time industrial environments requiring rapid decision-making [18], [20].

4.3 Distributed Architecture

Distributed architectures have gained significant importance in modern manufacturing industries due to their ability to support decentralized processing and intelligent decision-making.

Edge-Enabled Systems

Edge-enabled systems process industrial data locally near machines and production units. This architecture reduces communication delay and improves response time for real-time monitoring applications [11], [23].

Fog Computing

Fog computing extends cloud capabilities closer to industrial devices by introducing intermediate processing nodes between machines and cloud platforms. Fog systems provide:

- Low latency communication
- Faster data processing
- Improved reliability
- Reduced cloud dependency

Distributed architectures are highly suitable for large manufacturing environments where real-time monitoring and fast decision-making are critical [16], [17].

4.4 Cloud-Based Architecture

Cloud-based IoT architectures are widely used in smart manufacturing systems because they provide scalable computing resources and centralized industrial analytics.

Real-Time Analytics

Cloud platforms enable real-time:

- Energy monitoring
- Fault detection
- Predictive maintenance
- Production analytics
- Energy optimization

These systems help industries analyze large volumes of manufacturing data efficiently [12], [15].

Big Data Integration

Cloud architectures support big data technologies for:

- Industrial data storage
- Data mining
- Machine learning
- Historical trend analysis
- Process optimization

Cloud computing improves operational transparency and supports intelligent manufacturing systems [16], [23].

4.5 Hybrid Architectures

Hybrid architectures combine the advantages of cloud computing and edge computing to achieve efficient industrial energy monitoring.

Cloud + Edge Integration

In hybrid systems:

- Edge devices perform local processing
- Cloud platforms perform large-scale analytics
- Critical decisions are executed locally
- Long-term storage is managed in cloud systems

This integration improves:

- System scalability
- Response speed
- Data security
- Real-time monitoring efficiency

AI-Enabled Systems

Hybrid architectures are increasingly integrated with:

- Artificial Intelligence (AI)
- Machine Learning (ML)
- Digital Twin systems
- Predictive analytics

AI-enabled hybrid systems can automatically optimize industrial energy consumption and predict machine failures [12], [23].

4.6 Comparative Analysis of Architectures

Comparative Table of IoT Architectures

Architecture	Advantages	Limitations	Industrial Suitability
Centralized Architecture	Easy management, centralized analytics	High latency, scalability issues	Small and medium industries
Distributed Architecture	Low latency, fast processing	Complex implementation	Large manufacturing systems
Cloud-Based Architecture	Scalable storage and analytics	Internet dependency	Smart factories
Hybrid Architecture	Balanced processing and analytics	Higher implementation complexity	Advanced Industry 4.0 systems

The selection of architecture depends on industrial requirements such as scalability, response time, data security, and computational requirements [18], [20].

V. IoT Technologies Used in Smart Energy Monitoring

5.1 Sensors and Data Acquisition

Sensors form the foundation of IoT-based smart energy monitoring systems. They continuously measure industrial parameters and provide real-time operational data for monitoring and analytics [1], [5].

Types of Sensors

Current Sensors

Current sensors measure electrical current consumption of industrial machines and equipment. These sensors help identify energy-intensive operations and power losses.

Voltage Sensors

Voltage sensors monitor supply voltage variations and electrical disturbances affecting industrial equipment performance.

Temperature Sensors

Temperature sensors are used to monitor:

- Motor temperature
- Bearing temperature
- Process temperature
- Machine overheating conditions

Vibration Sensors

Vibration sensors are important for:

- Machine condition monitoring
- Predictive maintenance
- Fault diagnosis

- Bearing failure detection

Power Analyzers

Power analyzers provide detailed information about:

- Active power
- Reactive power
- Power factor
- Harmonics
- Energy quality

Suggested HD Figure

A high-resolution industrial sensor network diagram should include:

- Industrial machines
- Sensor nodes
- Controllers
- Wireless communication systems
- Cloud monitoring platform

5.2 Communication Technologies

Communication technologies enable real-time data transfer between industrial devices, controllers, cloud platforms, and monitoring systems [4], [10].

MQTT

MQTT is a lightweight communication protocol widely used in Industrial IoT systems due to:

- Low bandwidth requirement
- Fast communication
- Efficient real-time messaging

CoAP

CoAP is designed for resource-constrained IoT devices and supports lightweight industrial communication.

ZigBee

ZigBee provides:

- Low-power wireless communication
- Mesh networking capability
- Short-range industrial connectivity

Wi-Fi

Wi-Fi is commonly used for high-speed industrial data communication in smart factories.

LoRaWAN

LoRaWAN supports:

- Long-range communication
- Low power consumption
- Industrial remote monitoring

Bluetooth Low Energy (BLE)

BLE is suitable for short-range low-power industrial sensor communication.

OPC-UA

OPC-UA is an industrial communication standard providing:

- Interoperability
- Secure communication
- Industrial automation integration

Modbus

Modbus is one of the most widely used industrial communication protocols for machine-to-machine communication.

Comparative Table of Communication Protocols

Protocol	Range	Speed	Power Consumption	Industrial Use
MQTT	Medium	High	Low	Real-time monitoring
CoAP	Short	Moderate	Very Low	Lightweight IoT systems
ZigBee	Short	Moderate	Low	Sensor networks
Wi-Fi	Medium	High	High	Smart factories
LoRaWAN	Long	Low	Very Low	Remote monitoring
BLE	Short	Moderate	Very Low	Wearable and sensors
OPC-UA	Medium	High	Moderate	Industrial automation
Modbus	Short	Moderate	Low	Machine communication

5.3 Cloud Computing

Cloud computing plays a significant role in industrial energy management systems by enabling scalable storage and intelligent analytics [15], [23].

Major industrial cloud platforms include:

- AWS IoT
- Microsoft Azure
- Google Cloud IoT

Cloud systems support:

- Remote monitoring
- Data visualization
- AI integration
- Predictive analytics

- Energy optimization

5.4 Edge and Fog Computing

Edge and fog computing technologies reduce dependency on centralized cloud systems by processing industrial data near manufacturing equipment.

Low Latency Processing
Edge computing enables rapid processing of industrial data with minimal communication delay.

Real-Time Monitoring
These systems support:

- Real-time fault detection
- Instant alarm generation
- Local decision-making
- Fast machine response

Edge and fog computing are highly suitable for Industry 4.0 environments requiring fast and intelligent industrial operations [11], [17].

5.5 Big Data Analytics

Industrial IoT systems generate massive amounts of real-time manufacturing data. Big data analytics technologies help industries process, analyze, and optimize these datasets efficiently [16], [17].

Industrial Data Handling
Big data systems manage:

- Sensor data
- Machine logs
- Production data
- Energy consumption records
- Maintenance history

Data Storage Frameworks
Common data storage technologies include:

- Hadoop
- NoSQL databases
- Distributed cloud storage systems

Big data analytics improves:

- Predictive maintenance
- Process optimization
- Energy forecasting
- Decision-making accuracy

5.6 Cybersecurity Technologies

Cybersecurity is a major concern in Industrial IoT systems due to the increasing connectivity of manufacturing equipment [18], [29].

Encryption
Encryption techniques protect industrial data during transmission and storage.

Authentication
Authentication mechanisms ensure secure access to industrial monitoring systems and cloud platforms.

Intrusion Detection
Intrusion detection systems identify:

- Unauthorized access
- Network attacks
- Malware activities
- Abnormal industrial behavior

Strong cybersecurity frameworks are essential for ensuring reliable and secure industrial energy monitoring systems in smart manufacturing environments.

VI. Artificial Intelligence and Machine Learning Integration

6.1 AI in Energy Monitoring

Artificial Intelligence (AI) has become an important technology in IoT-based smart energy monitoring systems for manufacturing industries. AI techniques improve the ability of industrial systems to analyze large amounts of real-time operational data and make intelligent decisions automatically. AI-enabled monitoring systems support predictive analytics, fault diagnosis, energy optimization, and autonomous manufacturing operations [12], [20].

Predictive Analytics
Predictive analytics uses historical and real-time industrial data to estimate future operational conditions and energy consumption patterns. AI models can identify abnormal machine behavior, energy wastage, and process inefficiencies before major failures occur. Predictive analytics improves production planning, energy efficiency, and operational reliability [16], [17].

Fault Detection
AI-based fault detection systems continuously monitor industrial machines and detect abnormalities such as:

- Excessive power consumption
- Motor overheating
- Bearing failure
- Voltage fluctuation
- Machine vibration anomalies

Intelligent fault detection improves machine safety and reduces unexpected downtime in manufacturing systems [11], [18].

Energy Forecasting
AI algorithms are widely used for forecasting industrial energy demand and load variations. Energy forecasting helps industries:

- Optimize production schedules
- Reduce peak load consumption
- Improve energy utilization
- Minimize operational costs

Machine learning-based forecasting models provide better prediction accuracy compared to traditional statistical methods [9], [12].

6.2 Machine Learning Techniques

Machine Learning (ML) techniques enable industrial systems to learn from data and improve operational performance without explicit programming. ML algorithms are extensively used in Industrial IoT systems for predictive maintenance, process optimization, and energy analytics [5], [12].

Algorithms Used in Smart Energy Monitoring

Artificial Neural Network (ANN)

ANN models simulate the human brain structure for identifying complex relationships between industrial parameters and energy consumption. ANN is widely used for:

- Energy prediction
- Load forecasting
- Fault diagnosis
- Pattern recognition

Random Forest

Random Forest is an ensemble learning technique used for:

- Classification
- Predictive maintenance
- Failure analysis
- Process optimization

It provides high accuracy and robustness in industrial applications.

Support Vector Machine (SVM)

SVM algorithms are used for:

- Fault classification
- Anomaly detection
- Machine condition monitoring

SVM performs effectively for industrial datasets with nonlinear characteristics.

K-Nearest Neighbor (KNN)

KNN algorithms are useful for:

- Pattern recognition
- Predictive analytics
- Classification of machine operating conditions

Decision Trees

Decision tree models provide simple and interpretable decision-making structures for industrial monitoring systems.

Deep Learning

Deep learning models can process large industrial datasets and identify hidden patterns in manufacturing operations. Deep learning is highly suitable for:

- Predictive maintenance
- Real-time analytics
- Energy optimization
- Intelligent automation [16], [23].

6.3 Predictive Maintenance

Predictive maintenance is one of the most important applications of AI and machine learning in smart manufacturing systems. Predictive maintenance uses sensor data, AI algorithms, and machine learning models to monitor machine health and predict failures before breakdown occurs [17], [23].

Equipment Health Monitoring

Industrial IoT systems continuously monitor:

- Temperature
- Vibration
- Current consumption
- Lubrication conditions
- Machine utilization

Continuous monitoring helps evaluate the health condition of industrial equipment in real time.

Failure Prediction

AI-based predictive maintenance systems can identify early signs of machine failure and generate warning alerts for maintenance teams. This approach provides several benefits:

- Reduced downtime
- Lower maintenance cost
- Improved machine reliability
- Enhanced production efficiency
- Increased equipment life

Predictive maintenance significantly improves operational sustainability in Industry 4.0 manufacturing environments [11], [17].

6.4 Optimization Techniques

Optimization algorithms are widely used in industrial energy management systems for minimizing energy consumption and improving manufacturing efficiency. These algorithms optimize machine parameters, production scheduling, and operational conditions [20], [23].

Optimization Algorithms

Genetic Algorithm (GA)

Genetic Algorithm is an evolutionary optimization technique inspired by natural selection. GA is widely used for:

- Process parameter optimization
- Energy minimization
- Production scheduling
- Multi-objective optimization

Particle Swarm Optimization (PSO)

PSO is a population-based optimization technique that simulates swarm intelligence behavior. It provides:

- Fast convergence
- Efficient optimization
- Reduced computational complexity

PSO is commonly applied in energy-efficient manufacturing systems.

NSGA-II

Non-Dominated Sorting Genetic Algorithm-II (NSGA-II) is used for multi-objective optimization problems involving:

- Energy consumption
- Production efficiency
- Cost minimization
- Machine utilization

These optimization algorithms help industries improve sustainability and reduce energy wastage [12], [20].

6.5 Digital Twin Integration

Digital Twin technology has emerged as a powerful tool for smart manufacturing and industrial energy management systems. A Digital Twin is a virtual replica of physical industrial equipment and manufacturing systems that continuously interacts with real-time operational data [23].

Real-Time Simulation

Digital Twin systems perform real-time simulation of manufacturing processes using IoT sensor data. Real-time simulation helps industries:

- Monitor machine behavior
- Predict energy consumption
- Analyze operational efficiency
- Detect abnormalities

Virtual Energy Optimization

Digital Twin platforms support virtual optimization of manufacturing processes without interrupting actual production operations. Industries can test multiple operating conditions and identify energy-efficient process settings virtually before implementation.

Digital Twin integration improves:

- Process reliability
- Energy efficiency
- Decision-making capability
- Production optimization
- Smart factory automation [6], [23].

Suggested HD Figure

A high-resolution AI-enabled energy optimization framework should include:

- Industrial machines
- IoT sensors
- Data acquisition systems
- AI/ML analytics
- Cloud platform

- Digital Twin model
- Predictive maintenance module
- Energy optimization dashboard

VII. Applications in Manufacturing Industries

7.1 CNC Machining

CNC machining industries are among the major energy consumers in manufacturing sectors due to continuous operation of motors, spindles, cooling systems, and automation equipment. IoT-based smart energy monitoring systems help analyze machine-level power consumption and optimize machining parameters [12], [20].

Energy Monitoring in CNC Milling

IoT-enabled CNC milling systems continuously monitor:

- Spindle power consumption
- Feed motor energy
- Tool wear conditions
- Idle energy losses
- Cooling system energy usage

Real-time monitoring improves machining efficiency and reduces unnecessary energy consumption.

Real-Time Power Consumption

Real-time power monitoring helps industries:

- Optimize cutting parameters
- Reduce machine idle time
- Improve tool life
- Enhance production efficiency

AI and machine learning algorithms can further optimize CNC machining operations for sustainable manufacturing [6], [17].

7.2 Welding Systems

Welding processes consume significant electrical energy and generate thermal losses during industrial operations. IoT-based monitoring systems help improve welding efficiency and reduce energy wastage.

Energy-Efficient Welding Operations

Smart monitoring systems can analyze:

- Welding current
- Voltage variation
- Heat generation
- Welding cycle efficiency
- Electrode condition

These systems help optimize welding parameters and improve weld quality while minimizing energy consumption [20], [25].

7.3 Casting and Foundry

Casting and foundry industries consume large amounts of thermal and electrical energy in melting furnaces, molding operations, and material handling systems.

Furnace Energy Monitoring

IoT-based systems continuously monitor:

- Furnace temperature
- Fuel consumption
- Power utilization
- Heat losses
- Production efficiency

Smart monitoring improves thermal efficiency and reduces furnace operating costs in foundry industries [25], [28].

7.4 Additive Manufacturing

Additive manufacturing or 3D printing is an advanced manufacturing technology requiring precise energy control during material deposition processes.

Smart Monitoring in 3D Printing

IoT-enabled monitoring systems help analyze:

- Layer-wise energy consumption
- Temperature distribution
- Printing speed
- Material utilization
- Process stability

Smart monitoring improves product quality and energy efficiency in additive manufacturing systems [6], [20].

7.5 Process Industries

Process industries involve continuous manufacturing operations requiring efficient energy management systems.

Chemical Industries

IoT-based energy monitoring systems help optimize:

- Reactor temperature
- Pump operation
- Compressor energy
- Process heating systems

Textile Industries

Smart monitoring systems improve:

- Motor efficiency
- Energy consumption of spinning machines
- HVAC systems
- Production optimization

Food Processing Industries

Industrial IoT systems are used for:

- Refrigeration monitoring
- Process automation
- Energy-efficient processing
- Quality control

These applications improve industrial sustainability and operational efficiency [20], [25].

7.6 Smart Factory Applications

Smart factories represent highly automated and interconnected manufacturing environments integrating IoT, AI, cloud computing, and Cyber-Physical Systems [6], [26].

Integrated Manufacturing Systems
Smart factory applications support:

- Real-time production monitoring
- Autonomous machine communication
- Energy optimization
- Predictive maintenance
- Intelligent production scheduling
- Digital manufacturing

Integrated manufacturing systems improve:

- Productivity
- Energy efficiency
- Product quality
- Operational flexibility
- Sustainable manufacturing performance

Industrial IoT technologies are therefore playing a major role in transforming conventional industries into intelligent and energy-efficient smart manufacturing systems [21], [27].

VIII. Data Analytics and Performance Evaluation

8.1 Energy Performance Indicators

Energy performance indicators are essential for evaluating the effectiveness of IoT-based smart energy monitoring systems in manufacturing industries. These indicators help industries measure machine-level energy use, production efficiency, equipment performance, and sustainability improvement. In smart manufacturing, IoT sensors, cloud platforms, and big data analytics are used to collect and analyze real-time energy data for better decision-making [12], [16], [17].

Key Performance Indicators

- **Specific Energy Consumption (SEC):** SEC indicates the amount of energy consumed per unit of production. It is useful for comparing energy efficiency across machines, processes, or production batches. Lower SEC represents better energy performance.
- **Overall Equipment Effectiveness (OEE):** OEE evaluates equipment performance based on availability, performance rate, and quality rate. When combined with energy monitoring, OEE helps identify whether high energy consumption is linked with low productivity or machine downtime.

- **Energy Utilization Ratio:** This ratio shows how effectively the supplied energy is converted into productive manufacturing output. It helps identify idle energy losses, inefficient machine operation, and unnecessary auxiliary energy consumption.

8.2 Statistical Analysis

Statistical analysis is important for identifying relationships between process variables, machine conditions, and energy consumption. In IoT-enabled manufacturing systems, large volumes of data are collected from sensors and machines; statistical tools help convert this data into meaningful conclusions [12], [16].

Common Statistical Methods

- **Regression Analysis:** Used to develop mathematical relationships between input parameters such as current, voltage, speed, feed, temperature, and output energy consumption.
- **ANOVA:** Used to identify which process parameters have a significant effect on energy consumption and machine performance.
- **Correlation Analysis:** Used to study the strength and direction of relationships between variables such as machine load, power consumption, utilization, and production rate.

These techniques support data-driven manufacturing decisions and help improve energy efficiency through process optimization.

8.3 Real-Time Dashboards

Real-time dashboards are important components of IoT-based smart energy monitoring systems. They provide live visualization of machine energy consumption, power quality, production status, alerts, and performance indicators. Such dashboards help operators, supervisors, and energy managers quickly understand the energy behavior of manufacturing systems [1], [5], [15].

Main Functions of Dashboards

- Live monitoring of voltage, current, power factor, and energy consumption
- Machine-wise and process-wise energy visualization
- Alert generation during abnormal energy consumption
- Historical trend analysis
- Comparison of actual and expected energy use
- Support for maintenance and production planning

Energy Alerts

Energy alerts help detect:

- Sudden increase in power consumption
- Idle machine running
- Overload conditions
- Poor power factor
- Abnormal machine behavior

These alerts improve operational control and reduce energy wastage in manufacturing industries.

8.4 Energy Optimization Models

Energy optimization models are used to reduce energy consumption while maintaining productivity, product quality, and machine reliability. In smart manufacturing, mathematical models and multi-objective optimization techniques are integrated with IoT data to support intelligent decision-making [20], [23].

Mathematical Models

Mathematical models are developed to represent the relationship between:

- Machine operating parameters
- Production output
- Energy consumption
- Machine utilization
- Process efficiency

These models help predict energy demand and identify the best operating conditions.

Multi-Objective Optimization

Multi-objective optimization is useful when industries need to balance several goals at the same time, such as:

- Minimum energy consumption
- Maximum productivity
- Minimum cost
- Better machine utilization
- Reduced emissions

Algorithms such as Genetic Algorithm, Particle Swarm Optimization, and NSGA-II can be used for energy-efficient manufacturing decisions.

Suggested Table

Study	Industry	Methodology	Key Findings
Tao et al. [12]	Smart manufacturing	Data-driven manufacturing framework	Data analytics improves intelligent decision-making
Wan et al. [17]	Manufacturing	Big data and preventive maintenance	Improves reliability and maintenance planning
Qi and Tao [23]	Smart manufacturing	Digital Twin and big data	Supports real-time simulation and optimization
Kusiak [20]	Manufacturing	Smart manufacturing concept	Highlights intelligent and sustainable production

IX. Challenges and Limitations

9.1 Technical Challenges

IoT-based energy monitoring systems face several technical challenges during industrial implementation. Manufacturing environments include different machines, controllers, sensors, and communication systems, which often create problems of compatibility and integration [18], [29].

Major Technical Challenges

- **Interoperability:** Different machines and devices may use different communication standards, making integration difficult.
- **Sensor Reliability:** Sensors may fail due to heat, vibration, dust, electrical noise, or harsh industrial conditions.
- **Data Accuracy:** Incorrect sensor readings can affect energy analysis, prediction, and optimization results.

Reliable hardware, proper calibration, and standard communication interfaces are necessary to improve system performance.

9.2 Communication Challenges

Communication is a critical part of Industrial IoT systems. Data must be transmitted continuously from machines to edge devices, cloud platforms, and dashboards. However, industrial networks may face latency, packet loss, and connectivity issues [4], [10].

Common Communication Issues

- Network latency during real-time monitoring
- Packet loss in wireless communication
- Limited bandwidth in large-scale deployment
- Signal interference in industrial environments
- Difficulty in integrating legacy machines

Such issues can affect real-time decision-making and delay energy optimization actions.

9.3 Cybersecurity Risks

Cybersecurity is a major concern in IoT-based manufacturing systems because machines, sensors, cloud platforms, and dashboards are connected through industrial networks. Unauthorized access or cyber-attacks can disturb production, manipulate data, or damage industrial equipment [18], [29].

Key Cybersecurity Risks

- Data privacy issues
- Unauthorized access
- Malware attacks
- False data injection
- Cloud security risks
- Industrial network attacks

To reduce these risks, industries must use encryption, authentication, access control, firewalls, and intrusion detection systems.

9.4 Economic Challenges

Although IoT-based energy monitoring systems offer long-term benefits, their initial implementation cost can be high, especially for small and medium-scale industries.

Economic Barriers

- High cost of sensors and smart meters

- Cloud platform subscription cost
- Cost of software development
- Skilled manpower requirement
- Maintenance and calibration cost
- Uncertainty about return on investment

For SMEs, low-cost and scalable IoT solutions are necessary for wider adoption.

9.5 Scalability Issues

Scalability is another major challenge in large manufacturing industries. As the number of machines, sensors, and production lines increases, the system must handle large data volumes and continuous communication [16], [18].

Scalability Problems

- Increase in data storage requirement
- Higher network traffic
- More complex data processing
- Dashboard overload
- Difficulty in managing multiple plants

Edge-cloud hybrid architectures can help improve scalability by distributing data processing between local and cloud systems.

9.6 Standardization Issues

Lack of universal protocols and common standards is a major limitation in Industrial IoT implementation. Different manufacturers use different hardware, software, and communication protocols, which creates integration difficulties [4], [15].

Standardization Issues

- Lack of common industrial communication standards
- Difficulty in integrating legacy machines
- Vendor dependency
- Data format mismatch
- Limited interoperability among platforms

Standard protocols such as OPC-UA, MQTT, and Modbus can help improve industrial connectivity and system integration.

X. Comparative Review and Research Gap Analysis

10.1 Comparative Analysis of Existing Studies

A comparative review of existing studies shows that IoT, big data analytics, Digital Twin, CPS, and smart manufacturing technologies have significantly improved industrial monitoring and decision-making.

However, many studies remain limited to specific technologies or case-based applications rather than complete scalable energy monitoring frameworks [12], [18], [23].

Comparative Table

Author	Technology	Industry	Advantages	Limitations
Da Xu et al. [1]	IoT	Industrial systems	Provides broad IoT industrial framework	Limited focus on energy monitoring
Lee et al. [3]	CPS	Industry 4.0 manufacturing	Supports intelligent manufacturing architecture	Requires advanced integration
Wollschlaeger et al. [4]	Industrial communication	Automation networks	Explains future industrial communication	Implementation complexity
Tao et al. [12]	Data-driven manufacturing	Smart manufacturing	Enables intelligent decision-making	Requires large quality datasets
Wan et al. [17]	Big data	Manufacturing maintenance	Supports preventive maintenance	High data processing requirement
Boyes et al. [18]	IIoT framework	Industrial systems	Identifies IIoT challenges and framework	Security and interoperability concerns
Kusiak [20]	Smart manufacturing	Manufacturing	Highlights intelligent production systems	Needs practical implementation models
Qi and Tao [23]	Digital Twin and big data	Smart manufacturing	Supports real-time simulation	High computational requirement

10.2 Research Gaps

Although significant progress has been made in IoT-based smart manufacturing and energy monitoring, several research gaps still exist.

Major Research Gaps

- Limited development of real-time adaptive energy optimization systems
- Lack of integrated IoT, AI, edge, cloud, and Digital Twin frameworks
- Limited edge-AI implementation for local decision-making
- High computational requirements for big data and Digital Twin systems
- Limited practical studies on small and medium-scale manufacturing industries
- Insufficient focus on cybersecurity in energy monitoring systems
- Lack of standardized architecture for industrial energy monitoring

- Limited work on low-cost IoT solutions for SMEs

These gaps indicate the need for more practical, scalable, secure, and intelligent energy monitoring systems for manufacturing industries [17], [18], [23].

10.3 Critical Discussion

Existing literature shows that IoT-based smart energy monitoring systems have strong potential to improve energy efficiency, predictive maintenance, production planning, and sustainability in manufacturing industries. However, industrial implementation is still affected by technical, economic, communication, and cybersecurity barriers [18], [29].

Most existing systems focus either on data collection or monitoring, while limited studies provide complete closed-loop solutions for real-time energy prediction, optimization, and automated control. For future industrial needs, smart energy monitoring systems should become more adaptive, intelligent, affordable, and secure. Integration of AI, edge computing, Digital Twin, and standardized communication protocols will be essential for developing next-generation energy-efficient smart factories [12], [20], [23].

XI. Future Research Directions

11.1 AI-Driven Smart Manufacturing

Artificial Intelligence (AI) is expected to play a major role in the future development of smart manufacturing systems. AI-driven industrial systems can analyze large volumes of real-time manufacturing data and make intelligent decisions automatically without human intervention. Future manufacturing environments will increasingly depend on AI for autonomous process control, predictive maintenance, production scheduling, and energy optimization [12], [20].

Autonomous Energy Management
Future AI-enabled energy monitoring systems will support:

- Automatic load balancing
- Intelligent machine scheduling
- Real-time energy optimization
- Self-learning manufacturing systems
- Adaptive production planning

Autonomous energy management systems can reduce human dependency and improve industrial productivity, sustainability, and operational efficiency.

11.2 5G and Industrial IoT

The development of 5G communication technology is expected to significantly enhance Industrial IoT applications in manufacturing industries. 5G networks provide:

- Ultra-low latency
- High-speed communication
- Massive device connectivity
- Reliable industrial communication

These features are highly important for real-time industrial monitoring and autonomous manufacturing systems [10], [19].

Ultra-Low Latency Monitoring
Future Industrial IoT systems integrated with 5G technology will support:

- Real-time machine communication
- Instant fault detection
- Fast industrial automation
- Remote robotic operation
- Smart factory synchronization

5G-enabled monitoring systems will improve industrial responsiveness and support large-scale smart manufacturing environments.

11.3 Blockchain Integration

Blockchain technology has emerged as a promising solution for improving security, transparency, and reliability in Industrial IoT systems. Blockchain creates decentralized and tamper-resistant data storage systems for industrial applications.

Secure Energy Transactions

Blockchain-based industrial systems can support:

- Secure industrial data sharing
- Transparent energy transactions
- Decentralized energy management
- Secure machine communication
- Reliable supply chain monitoring

Future smart factories may use blockchain to improve cybersecurity and trust in industrial energy management systems [18], [29].

11.4 Green Manufacturing

Green manufacturing is becoming an important research direction due to increasing environmental concerns and global sustainability goals. Industries are focusing on reducing energy consumption, minimizing waste generation, and lowering greenhouse gas emissions [25], [28].

Carbon Footprint Reduction

Future green manufacturing systems will emphasize:

- Renewable energy integration
- Energy-efficient production systems
- Carbon emission monitoring
- Waste heat recovery
- Sustainable resource utilization

IoT-based energy monitoring systems will help industries continuously monitor and reduce their environmental impact.

11.5 Digital Twin-Based Energy Optimization

Digital Twin technology is expected to become one of the most important technologies for future smart manufacturing systems. Digital Twin creates virtual replicas of industrial machines and manufacturing systems using real-time sensor data [23].

Virtual Process Optimization
Digital Twin systems can support:

- Virtual machine simulation
- Real-time process monitoring
- Predictive energy analysis
- Process parameter optimization
- Failure prediction and maintenance planning

Future Digital Twin platforms integrated with AI and IoT technologies will improve industrial energy efficiency and manufacturing flexibility.

11.6 Sustainable Smart Factories

Future manufacturing industries are expected to evolve toward sustainable smart factories integrating Industry 4.0 technologies, renewable energy systems, AI, IoT, cloud computing, and advanced automation [6], [26].

Net-Zero Manufacturing Systems
Future smart factories will focus on:

- Net-zero carbon emissions
- Energy-efficient automation
- Circular manufacturing systems
- Intelligent energy management
- Sustainable production planning

Sustainable smart factories will contribute toward global environmental protection and long-term industrial sustainability.

XII. Industrial Implications

12.1 Benefits to Manufacturing Industries

IoT-based smart energy monitoring systems provide significant benefits to manufacturing industries by improving operational efficiency, reducing energy wastage, and supporting sustainable manufacturing practices [20], [25].

Major Industrial Benefits

Energy Savings
Real-time energy monitoring helps industries identify:

- Idle machine operation
- Excessive power consumption
- Inefficient manufacturing processes
- Energy losses in production systems

This leads to significant reduction in industrial energy consumption.

Cost Reduction
Energy-efficient manufacturing systems help reduce:

- Electricity bills

- Maintenance costs
- Machine downtime
- Production losses

IoT-enabled predictive maintenance further reduces repair expenses and unexpected equipment failures.

Improved Efficiency
Smart manufacturing systems improve:

- Machine utilization
- Production planning
- Process optimization
- Operational reliability
- Product quality

Industries can achieve higher productivity through data-driven decision-making and intelligent automation [12], [17].

12.2 Benefits to SMEs

Small and Medium Enterprises (SMEs) often face challenges related to limited financial resources, inefficient energy management, and lack of advanced industrial automation technologies. IoT-based energy monitoring systems provide affordable and scalable solutions for SMEs [20], [28].

Affordable Monitoring Systems
Low-cost IoT technologies help SMEs:

- Monitor machine-level energy consumption
- Improve process efficiency
- Reduce operational cost
- Enhance equipment reliability
- Increase production competitiveness

Cloud-based and wireless monitoring systems reduce infrastructure costs and improve accessibility for small industries.

12.3 Policy and Sustainability Implications

Governments and industrial organizations are increasingly promoting sustainable manufacturing practices through environmental regulations, ESG policies, and energy efficiency standards.

ESG Compliance
IoT-based smart energy monitoring systems support:

- Environmental monitoring
- Carbon emission reduction
- Sustainable production reporting
- Industrial energy auditing

Industries can use IoT-based systems to improve compliance with Environmental, Social, and Governance (ESG) frameworks.

Sustainable Development Goals
Smart manufacturing technologies contribute toward several sustainable development goals including:

- Affordable and clean energy
- Industry innovation and infrastructure
- Responsible consumption and production
- Climate action

Industrial IoT technologies therefore play a major role in achieving sustainable industrial growth [25], [28].

XIII. Industrial Implications

The present review article provides a comprehensive analysis of IoT-based smart energy monitoring systems in manufacturing industries. The study highlights the growing importance of Industrial IoT, smart manufacturing, Artificial Intelligence, cloud computing, edge computing, Digital Twin technology, and Cyber-Physical Systems in improving industrial energy efficiency and operational sustainability [6], [20].

The review shows that IoT-enabled monitoring systems provide several advantages such as:

- Real-time energy monitoring
- Predictive maintenance
- Intelligent fault detection
- Production optimization
- Reduced energy consumption
- Improved machine utilization

Advanced technologies such as AI, machine learning, big data analytics, and Digital Twin integration are transforming conventional manufacturing systems into intelligent smart factories capable of autonomous decision-making and adaptive energy optimization [12], [23].

The review also identifies several important challenges associated with Industrial IoT implementation, including:

- Interoperability issues
- Cybersecurity risks
- Network latency
- High implementation cost
- Scalability limitations
- Lack of standardization

Despite these challenges, future research opportunities remain significant in areas such as:

- AI-driven autonomous manufacturing
- Edge-AI systems
- Blockchain-enabled industrial security
- 5G-based Industrial IoT
- Sustainable smart factories
- Net-zero manufacturing systems

Overall, IoT-based smart energy monitoring systems have strong industrial significance because they support sustainable manufacturing, improve production efficiency, reduce operational cost, and contribute toward environmentally responsible industrial development. The integration of intelligent monitoring technologies will continue to play a major role in the future evolution of Industry 4.0 and next-generation smart manufacturing systems [21], [26], [28].

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