Chapter 6 / Capítulo 6

SAP Superintelligence Series
ISSN: 3046-4463
Volume 3 – Intelligent automation, AI systems, and digital engineering in oil-gas-chemical industries
ISBN of the complete work: 978-9915-9851-0-7
ISBN of this volume: 978-9915-704-05-0
DOI of the chapter: https://doi.org/10.62486/978-9915-9851-0-7_202636
Pages: 95-113

©2026 The authors. This is an open access article distributed under the terms of the Creative Commons Attribution (CC BY) 4.0 License.

ORIGINAL

Smart Energy Management and Automation Systems: Emerging Directions in Manufacturing and the Oil-Gas-Chemical Industries

Sistemas inteligentes de gestión de energía y automatización: nuevas direcciones en la fabricación y las industrias del petróleo, el gas y la química

Hariprasad Perumal[1] ✉, Jeevarathinam A[2] ✉, Karan R[1] ✉, Jegan Karthik S[1] ✉, Gokulnath P[1] ✉, Prabhu P[1] ✉, Malikov Ziyodullo Abdurayim[3] ✉

[1]Department of Mechanical Engineering, KIT-Kalaignarkarunanidhi Institute of Technology. Coimbatore-641402, Tamil Nadu, India.

[2]Department of Mechanical Engineering, Hindusthan Institute of Technology. Coimbatore-641032, Tamil Nadu, India.

[3]Teaching Assistant, Department of Software Engineering, Faculty of Artificial Intelligence and Digital Technologies. Samarkand State University, Uzbekistan.

Corresponding Author: Hariprasad Perumal ✉

ABSTRACT

In the wake of changes in industrial engineering, the manufacturing, oil-gas-chemical sectors have rapidly adopted smart energy management coupled with automation technologies. Although these fields have mostly taken different technological routes, the need to reduce operational costs, increase the system's reliability, and meet strict sustainability requirements has led to a considerable blending of these technologies. This review consolidates the innovations in smart monitoring, real-time control, and predictive optimization that are largely driven by digital platforms, sensor-equipped infrastructures, and data-driven decision-making frameworks. This framework includes three layers of the proposed architecture which is device, edge and cloud, encompassing automation devices and sensors, a secure communication protocol (MQTT, OPC-UA, Modbus TCP/IP) and AI analytic for big data handling. This research provides a structured analysis of various topics, including implementation processes, data veracity, cyber security, and case studies involving automotive and pharmaceutical sectors. The Energy Management System (EMS) based on IoT systems provides a reduction in energy use of between 18-25 %, a reduction in downtime of about 22-35 %, and a reduction in maintenance costs of about 15-30 %. The paper concludes with discussions on barriers to adoption including interoperability of legacy systems, veracity of data, and developing an effective human-machine interface. In addition, we share our thoughts on the integration of renewable energy systems, digital twins, and predictive maintenance systems .The results agree that a manufacturing facility can achieve a ROI within 8-14 months and meet its sustainability targets with respect to an ISO 5001 Organizational Energy Management System (EnMS) and UN Sustainable Development Goal (SDG) invitations aligned with the study.

Keywords: Internet of Things; Energy Monitoring; Manufacturing; Edge Computing; Predictive Maintenance; Sustainability; Industry 4.0.

RESUMEN

A raíz de los cambios en la ingeniería industrial, los sectores manufacturero, petrolero, gasístico y químico han adoptado rápidamente la gestión inteligente de la energía, junto con tecnologías de automatización. Si bien estos campos han adoptado, en su mayoría, diferentes caminos tecnológicos, la necesidad de reducir los costos operativos, aumentar la confiabilidad del sistema y cumplir con los estrictos requisitos de sostenibilidad ha llevado a una considerable integración de estas tecnologías. Esta revisión consolida las innovaciones en monitorización inteligente, control en tiempo real y optimización predictiva, impulsadas en gran medida por plataformas digitales, infraestructuras con sensores y marcos de toma de decisiones basados en datos. Este marco incluye tres capas de la arquitectura propuesta: dispositivo, borde y nube, que abarcan dispositivos y sensores de automatización, un protocolo de comunicación seguro (MQTT, OPC-UA, Modbus TCP/IP) y análisis de IA para el manejo de big data. Esta investigación proporciona un análisis estructurado de diversos temas, incluyendo procesos de implementación, veracidad de datos, ciberseguridad y casos prácticos relacionados con los sectores automotriz y farmacéutico. El Sistema de Gestión de Energía (SGE) basado en sistemas IoT ofrece una reducción del consumo energético de entre un 18 % y un 25 %, una reducción del tiempo de inactividad de entre un 22 % y un 35 % y una reducción de los costes de mantenimiento de entre un 15 % y un 30 %. El artículo concluye con un análisis de las barreras para su adopción, como la interoperabilidad de los sistemas heredados, la veracidad de los datos y el desarrollo de una interfaz hombre-máquina eficaz. Además, compartimos nuestras reflexiones sobre la integración de sistemas de energía renovable, gemelos digitales y sistemas de mantenimiento predictivo. Los resultados coinciden en que una planta de fabricación puede alcanzar un retorno de la inversión (ROI) en un plazo de 8 a 14 meses y cumplir sus objetivos de sostenibilidad con respecto a un Sistema de Gestión de Energía Organizacional (SGE) ISO 5001 y las invitaciones a los Objetivos de Desarrollo Sostenible (ODS) de las Naciones Unidas, alineados con el estudio.

Palabras clave: Internet de las Cosas; Monitorización de la Energía; Fabricación; Edge Computing; Mantenimiento Predictivo; Sostenibilidad; Industria 4.0.

INTRODUCTION

Motivation and Problem Statement

Manufacturing plants are one of the biggest energy-consuming sectors in the world, representing approximately 30 % of all energy consumed in industrial settings. Even with some advancements in technology energy waste continues to be a significant issue, with estimates suggesting 20-30 % of the energy used by manufacturing facilities is wasted[1] through various types of inefficiencies(e.g. equipment failure, phantom loads, and improper process parameters). Traditional energy management strategies rely on audits at regular intervals and collecting manual (or automated) data, which severely limit visibility into real-time usage patterns and, as a result, only allow for 5 % energy savings rather than 20 % from continuous real-time monitoring.[2] The combination of predicted energy cost increases, carbon reductions driven by environmental regulations, and global national sustainability initiatives has changed energy efficiency from being a cost savings measure to becoming a strategic initiative for manufacturing organizations. Additionally, new and emerging Industry 4.0 technologies (i.e. IoT devices, edge computing and artificial intelligence devices) have provided massive increases in visualization and control over manufacturing processes.[3,4] The rapidly digitalized industrial processes have in a fundamental way changed the standards of efficiency, reliability and environmental regulations requirements in the sectors of manufacturing and oil–gas–chemical. The use of integrated sensing, data

analytics, and automated control, a smart energy management system is viewed as a must-have tool for not only energy saving but also for stabilizing plant performance under fluctuating operating conditions. Such platforms allow manufacturing the energy consumption to be very detailed, predictive load assessment to be conducted, and the correlation between process scheduling and energy availability to be strengthened. The same kind of innovations in the oil and gas sector show a similar transition to data-centric process control, where it is being gradually automated frameworks to be implemented for drilling operations, equipment monitoring, and production scheduling in order to reduce the time when the plant is not working and lessen the operational risk. These features together signal a massive shift toward intelligent, self-regulating industrial systems that not only can raise productivity levels but also contribute to the achievement of sustainability goals. Meanwhile, the oil and gas sector is also investing in similar future-proof technologies like additive manufacturing, smart materials, and polymer-based performance enhancers not only to make equipment more reliable but also to become more efficient in the subsurface recovery. The recent publications clearly show how innovations at the component level, e.g. the use of additively manufactured tools and repair parts, can very quickly change the face of the maintenance operations and shorten the supply-chain delays which are typical of extraction and gathering activities. Similarly, smart polymer systems and eco-friendly composite formulations are leading us to different sources of both increasing the recovery efficiency and decreasing the chemical footprints. These emerging technologies together with the implementation of intelligent monitoring and automation infrastructures paint the picture of a gradually interconnected industrial landscape where energy management, material innovation, and automated control are the three interdependent pillars supporting each other. Ultimately, this convergence calls for a systemic review of the manufacturing and the oil–gas–chemical industries trends of today and tomorrow.

Research Objectives

This study outlines the design, execution, and enhancement of IoT-based energy monitoring frameworks to be implemented in manufacturing settings. The key goals are:

1. To develop a complete three-layered IoT architecture that incorporates sensor networks, edge computing infrastructure, and cloud analytics systems to monitor energy in real time.
2. To identify and address key implementation issues such as legacy system interoperability, data quality assurance, and cybersecurity weaknesses.
3. To assess the quantitative benefits of IoT-based energy management through case studies revealing verifiable energy efficiency, equipment reliability, and operating costs improvements.
4. To develop integration strategies with renewable energy systems, proactive maintenance frameworks, and AI optimized automations.
5. To identify best practices for data validation, machine-human interface work, and lifecycle management to provide prolonged system performance and user adoption.

Literature Review and Theoretical Foundation

Evolution of Energy Management Systems

Energy management processes in manufacturing have been revitalized according to four distinct paradigms. The old way of doing things revolved around manual readings of meters and annual energy audits, which offered real-time monitoring but ultimately limited visibility, and energy management took a reactive approach rather than a proactive role. The transition to the next paradigm of advanced metering infrastructure and distributed control systems represented the second paradigm, but while organizations were automating monitoring in real-

time, they were still often orchestrating siloed actions in various departments or on production lines. Industrial IoT (IIoT) technologies then disrupted this category of energy management to enable pervasive networks of sensors to collect detailed and time synchronized data points from each piece of equipment in the manufacturing environment, and when connectivity to the edge and cloud analytics were also no longer complicated, data analysis was much easier[5] not only because of all the data but the visualization and analytics that can be performed on a continuous basis. As a function of advancing technology in energy management, the process evolved from a passive monitoring function toward an active and adaptive optimization system to drive visibility and real-time decision making.[6,7]

The evolution of energy management systems in oil production has gone through various stages, which were influenced by technological innovations and the need for efficiency. Initially, the plants were operated manually, and the technicians of the plants controlled the equipment by using simple gauges, analog instruments, and their own observation as shown in figure 1. The decisions were mostly made based on the experience of the staff, energy consumption was reactive, and the energy was not optimized. Even though this method guaranteed the basic operation, it did not allow the facility to monitor energy losses or to intervene before inefficiencies increased.

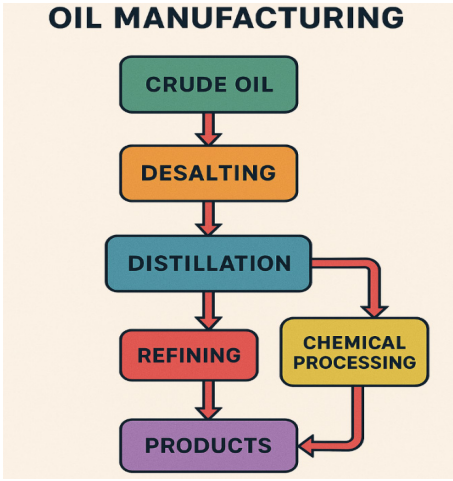


Figure 1. Stages in the evolution of energy management systems in oil manufacturing

Automation introduction was a drastic change. The use of Programmable Logic Controllers (PLCs), digital sensors, and automated monitoring instruments made process control more dependable and error-free, and also provided continuous data streams. This stage was a platform for comprehending energy consumption in machinery such as pumps, heaters, compressors, and distillation units. However, the main emphasis of automation was on process stability, and energy optimization was only a minor, incidental benefit.

Machine Learning and Predictive Analytics

Machine learning algorithms have greatly changed energy management from reactive corrective maintenance to proactive predictive optimization: predictive maintenance systems that analyze equipment vibration signatures, acoustic patterns, temperature differentials and anomalies in power consumption can detect incipient equipment failures 3-8 weeks before the breakdown occurs,[9,10] reduce unplanned equipment downtime by 35-45 %, and cut maintenance costs by 25-30 %. Similarly, energy consumption forecasting is implemented utilizing a time-series model, including:

Table 1. Machine Learning Models for Energy Prediction

ML Model	Prediction Accuracy	Training Time	Data Requirements	Computational Load	Best For	Advantages	Limitations
LSTM Networks	94-97 %	2-4 hours	6+ months historical	Medium-High	Time-series forecasting	Captures long-term dependencies	Requires significant data
XGBoost	91-95 %	30-60 min	3+ months historical	Medium	Non-linear patterns	Fast training, feature importance	Less suitable for very long sequences
Random Forest	88-93 %	15-30 min	2+ months historical	Low-Medium	Feature interactions	Interpretable, handles missing data	Limited temporal pattern capture
ARIMA	85-90 %	<5 min	2+ months historical	Low	Linear trends	Simple, interpretable	Assumes stationarity
Hybrid ARIMA-ANN	92-96 %	1-2 hours	4+ months historical	Medium	Complex temporal patterns	Combines strengths of both	More complex to tune
Support Vector Machine (SVM)	89-92 %	20-40 min	3+ months historical	Medium	High-dimensional data	Robust to outliers	Slower prediction
Neural Networks	90-94 %	30-90 min	3+ months historical	Medium	General-purpose forecasting	Flexible architecture	Risk of overfitting

IoT Architecture and Communication Protocols

Modern implementations of IoT technologies for energy monitoring typically use a multi-layered architecture with four layers: perception, network, processing, and application layers. The perception layer consists of a range of sensors, both current and potential transformers (CT and PT), smart power meters, and environmental sensors (temperature, humidity, and pressure) that sample electrical and operational parameters at high frequency.

Edge Computing and Distributed Analytics

Edge computing is a new way of organizing computational resources, unlike cloud-centric processing. Edge converts intelligence to where data is created, the source, and away from a centralized processing node. In energy monitoring scenarios, edge gateways act as preprocessing units to filter noise, detect anomalies, compress data, and extract features. Edge computing can reduce bandwidth requirements by up to 80 % while supporting decision-making needed at lower latency.[8]

Proposed System Architecture

Three-Layer IoT Framework

The proposed architecture consists of three functionally distinct layers that are hierarchically integrated in a manner which addresses special technical needs.

Device Layer (Perception and Measurement)

The device layer perceives electrical and operational measurements using different kinds of sensors.

Electrical Measurement Components:

1. Current Transformers (CT): they reduce high-value (industrial) currents into low-value signals (0-5V or 4-20 mA) for digital transmission and preserve electrical isolation.[11,12]

2. Potential Transformers (PT): they step down three-phase power from operational voltage (208-480V) to a measurement voltage (0-110V).

3. Smart Power Meters: an Integrated IED (Intelligent Electronic Devices) which measures voltage, current, frequency, power factor, active/reactive/apparent power, and harmonic content; sampling (1-4 KHz).[13]

Sensor Selection Strategy:

Table 2. Energy Monitoring Sensors - Device Characteristics and Deployment Options

Device Type	Application	Characteristics	Advantages
Wired Smart Meters	Fixed heavy machinery	High reliability, stable data quality	±0,1 % accuracy, continuous operation
Wireless IoT Sensors	Mobile equipment, retrofits	Flexible deployment, rapid installation	Minimal infrastructure changes, LoRa/ZigBee/ Wi-Fi options
CT/PT Combinations	Main switchgear monitoring	Fundamental measurement infrastructure	Electrical isolation, standard industrial practice
Environmental Sensors	Process optimization	Temperature, humidity, pressure	Correlation analysis with energy consumption

Sampling Rate Optimization

Selecting a sampling rate involves a tradeoff between measurement accuracy and limitations on network bandwidth. Sampling at a high-frequency rate (4 kHz) collects harmonic distortion and transients that are important to evaluating power quality, but achieves a daily data rate of 345,6 MB per meter for 24-bit resolution over a 24-hour period. Sampling at an intermediate rate (100 Hz) will record sub-cycle events while reducing traffic to 8,6 MB per meter on a daily basis. Intelligent variable rate sampling dynamically switches sample rates based conditions on the grid and anomalies that have been detected.

Edge Layer (Local Processing & Intelligence)

Edge gateways are intelligent intermediaries that do real-time analysis and decision making at the 'edge'

Main Functions:

1. Data Aggregation: synchronizes measurements from diverse sensors to a common time-base using either Network Time Protocol (NTP) or Global Positioning System (GPS) based synchronization.
2. Signal Conditioning: filters noise (low-pass Butterworth filters), detects outliers (Z-score, Isolation Forest), and imputes missing values.
3. Feature Computation: computes derived features: power factor (cos φ), total harmonic distortion (THD), peak demand, load factors.
4. Anomaly Detection: runs real-time unsupervised learning algorithm (Isolation Forest, Local Outlier Factor) to identify consumption anomalies within seconds.[14]
5. Local Storage: configurable buffer (24-72 hours) enabling autonomous operation during network disconnection.
6. Bidirectional Communication: receives commands from cloud platforms (recalibrate and update algorithms) and executes local control actions (switch load, alert).

Cloud Layer (Advanced Analytics and Strategic Visualization)

Cloud Layer (Higher-Level Analytics & Visual Analytics)-Execution of analytics that takes place over the long-term, identification of patterns, and optimizations across the system-level for the cloud.

Data Processing Pipeline:

1. Ingestion: receives data from the Edge through message brokers (e.g., Apache Kafka, AWS Kinesis) capable of throughput at 100K+ messages/second.[15]
2. Time-Series DB: data flows into the specialized Time-Series DB that stores the pre-processed data (e.g., InfluxDB, TimescaleDB, AWS Timestream); optimized for temporal separate responses to temporal queries
3. Historical Analytics: provides computation on performance trends, detects seasonal types of patterns, and provide deviation from baseline or expectations to SQL and distributed computing (e.g., Apache Spark, Presto).
4. Predictive Models: provides execution of trained machine learning models (e.g., LSTM, XGBoost, Random Forest) for both energy forecasting and anomaly detection.
5. Visualization & Reporting: generates interactive dashboards (e.g., Grafana, Power BI, custom web interface) as well as compliance reporting.

Communication Protocol Strategy

The strategy uses protocol layering to maintain backward compatibility while allowing for current interoperability:

Table 3. Legacy Equipment Integration - Protocol Conversion Strategies for IoT Systems			
Legacy Equipment	**Adapter Type**	**Protocol Out**	**Modern System**
Old PLC (Modbus RTU)	Serial-to-Ethernet converter	Modbus TCP/IP	Edge Gateway
20+ Year Analog Meters	Pulse-to-MQTT gateway	MQTT	Cloud Platform
SCADA Systems	OPC-UA Bridge	OPC-UA → MQTT	Cross-Platform Analytics

Semantic interoperability is implemented by mapping data model elements so that "voltage in phase A" represents the same concept, regardless of the source device.[16] Additionally, node defined architectures are outlined by OPC UA with semantic meanings, while MQTT transport efficiently manages dissemination of the messages

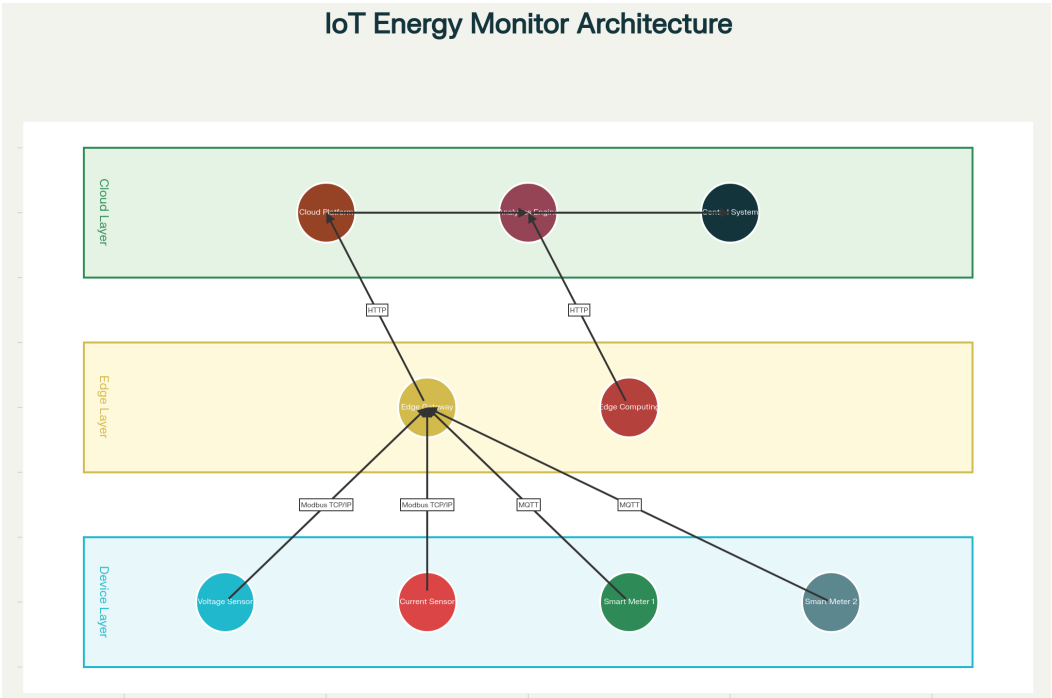


Figure 2. Three-Layer IoT Architecture for Smart Energy Monitoring in Manufacturing Plants

Implementation Methodology

Phased Deployment Strategy

In order to successfully implement IoT energy monitoring, you need to go through a structured set of steps which are broken down into clearly defined phases that build on the results of prior steps and validate your assumptions before fully committing operational costs. The framework breaks implementation into three phases that take approximately 18 months from initiation to full operational capability.

The deliverables expected from phase 3 would be energy reduction maintained at a 25-30 % level across activities/assets within facility operation, maintenance cost reduction from a predictive maintenance approach deployed at scale estimated at 30-40 %, 8-12 % additional savings through optimization of renewable utilization, and continuous autonomous energy management lines run with human oversight acting as a trusted and safe authority for plant operations.

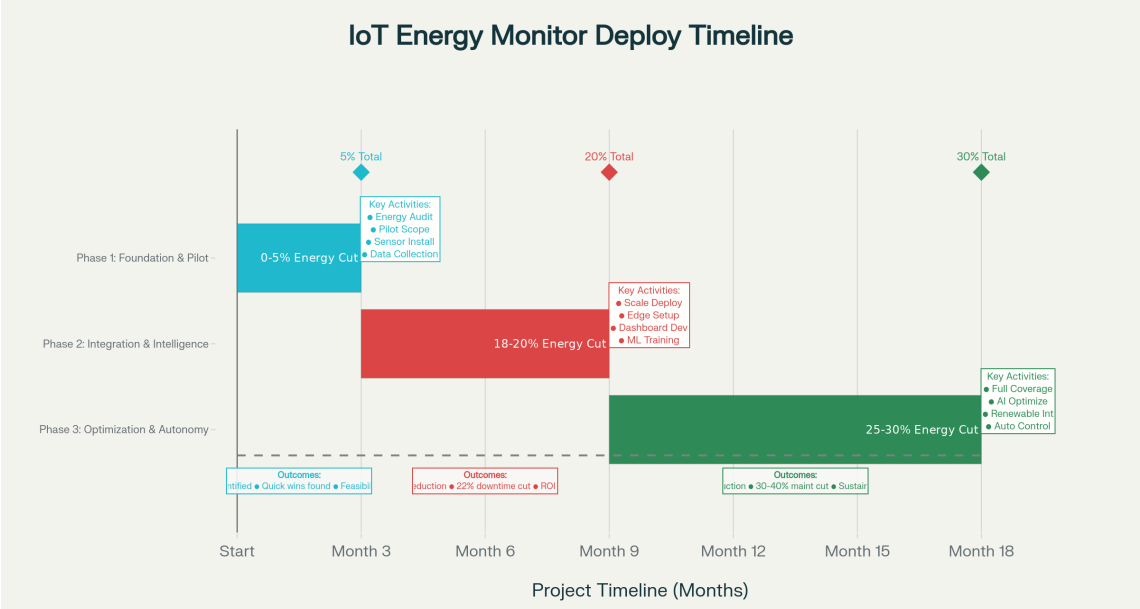


Figure 3. Three-Phase Implementation Roadmap for IoT Energy Monitoring Systems (18-Month Timeline with Cumulative Benefits)

Cybersecurity Architecture

IoT energy systems are a valuable attack target because of the sensitive operational data and authority they possess. A defense-in-depth approach addresses multiple threat vectors:

Authentication and Access Control:[17,18]

1. Device Authentication: X.509 certificates issued to each sensor/edge device, Certificate-based mutual authentication for MQTT connections, Hardware Security Modules (HSM) on critical devices for storage of keys.
2. User Authentication: multi-factor authentication (MFA) for access to the dashboard: factors including knowledge (password), possession of (phone authenticator), inherence (biometric), Role-Based Access Control (RBAC) and principle of least privilege.
3. API Authentication: auth 2.0 for third-party integrations, API key rotation compliance (quarterly minimum).

Authentication for third-party API integrations adheres to OAuth 2.0 standards with a key rotation policy that at least renews quarterly. TLS 1.3 is required for all data in transit between architectural layers, with the implementation of perfect forward secrecy (PFS) mechanisms which negate the potential compromise of historic communications by future key theft. Data at rest encrypts historical data and configurations stored in the cloud using AES-256 with database level encryption using separate key management that is distinct from ongoing operations.[19,20] Network segmentation separates edge gateways in a demilitarized zone (DMZ) from general IT networks with firewalls restricting connectivity to MQTT brokers only. Energy monitoring traffic trains in separate VLAN (Virtual Local Area Network) using segregation to restrict lateral movement by any IT system that has been compromised.[21,22]

Firewall rules permit inbound only MQTT (ports 1883/8883), NTP (123), and other monitoring protocols while restricting outbound communications to whitelisted cloud endpoints that are configured using IP address and fully qualified domain name patterns. An intrusion detection system monitors for suspicious patterns that include unusual geographic login locations or atypical

frequency of API calls which generate alerts for further investigation. Audit logging records are immutable, retaining records of system access, configuration changes, and anomalies for the last 12+ months to support forensic analysis and regulatory compliance. Incident response procedures describe breach scenarios which include timelines for notification, isolation, and recovery. Research has shown that organizations who encompass coverage of comprehensive proportion of cybersecurity controls would increase operational costs by 12-18 % but prevent breaches that would incur operational disruption, pricing as work stoppage quantity of 50-200 times that amount along with government-imposed fines.

Table 4. Cybersecurity Controls and Compliance Requirements

Security Control	Implementation Method	Compliance Standard	Verification Method	Risk Level if Missing	Update Frequency
Device Authentication	X.509 Certificates	IEC 62351-3	Certificate validation	Critical	Quarterly
Data Encryption (Transit)	TLS 1.3 with PFS	NIST SP 800-52	SSL/TLS scan	Critical	Continuous
Data Encryption (Rest)	AES-256	NIST FIPS 140-2	Encryption audit	High	Quarterly
User Authentication	Multi-Factor (MFA)	ISO/IEC 27001	Login attempt audit	High	Monthly
Access Control (RBAC)	Role-based permissions	ISO/IEC 27001	Permission matrix review	High	Semi- annually
Firewall Rules	Whitelist policies	CIS Controls	Firewall rule audit	High	Monthly
Intrusion Detection	Behavioral anomaly detection	NIST SP 800-61	Alert log review	Medium	Weekly
Audit Logging	Immutable logs (12+ months)	GDPR/ISO 27001	Log retention verification	High	Monthly

Case Studies and Quantitative Validation

Steel Manufacturing Facility (18-Month Implementation)

A large-scale steel production facility has a total annual output of over 50 000 tons of steel representing 12-14 % of the regional steel output rate and took part in nationwide, comprehensive IoT energy monitoring. The energy consumers of this facility consisted of arc furnaces, which consumed 38 % of overall consumption; followed by rolling mills, consuming 25 %; and cooling systems accounting for 18 % of chemical plant electrical loads. The baseline energy intensity for the plant's operations was 0,85 megawatts-hours per ton of output, and the annual energy cost for the facility was $4,2 million prior to the implementation of optimization. The facility's industrial machinery was representative of a typical mix of industrial equipment with a large range of vintage, creating interoperability issues that are associated with older, mature manufacturing plants. Equipment downtime reduction was 22 % when measured from the baseline of before implementation and there were 8 major failures avoided due to early anomaly detection. Maintenance costs savings were $180 000 per year (25 % reduction) due to a shift to condition-based maintenance from being calendar-based. Value of production interruptions avoided from early detection of failures was estimated at $450 000+; which avoided value of late customer shipment and inventory write-offs. Total implementation cost including sensors, edge hardware, software, and implementation labor was $165 000. Annual savings (energy and maintenance) equaled $262 000 for a simple payback period of 7,5 months. Cumulative 3-year savings were $786 000 with net present value of $541 000 (10 % discount

rate). One key insight from the implementation was cooling system optimization had the biggest single opportunity (38 % of total savings) and illustrated value of choosing pilot projects that target the biggest energy consumer. The predictive maintenance algorithms trained on 9 months of data demonstrated 89 % accuracy at predicting bearings to failure 4-8 weeks ahead. Operator engagement improved significantly after training; operators on the floor identified 6 additional optimization opportunities that were not identified from the engineering analysis.

Pharmaceutical Manufacturing Plant (12-Month Implementation)

A pharmaceutical manufacturing facility uniquely focused on clean room production in temperature-controlled spaces was capable of maintaining the required temperature range of 18-24°C and 40-60 % relative humidity by operating advanced HVAC systems throughout production. Equipment in the facility included four chillers and three boiler units and predominately consumed energy via its HVAC systems, which accounted for 65 % of the overall facility energy consumption. The baseline energy intensity at the facility was $180 per unit of active pharmaceutical ingredient produced, and the facility was spending ~$2,8 million annually on energy expenditures prior to the IoT implementation. In relation to process requirements for strict environmental adherence, there were very slight margins for manufacturing flexibility, complicating both demand response opportunities and load shifting planning. The pharmaceutical facility was engaged in the broader SMARTEE industrial IoT project making use of common submetering infrastructure and research protocol from the previous steel facility . The implementation time-frame was reduced to 12 months in contrast with the first facility, and the scope of equipment sophistication was less than the steel facility's variant of the IoT implementation timeline of 18-months. The facility's cloud platform selection was ThingSpeak using the MQTT protocol. Edge devices used were Raspberry Pi with Node-RED for local data processing. Sensors included IoT-enabled submeters for critical equipment, Modbus over RS-485 for legacy equipment and MQTT for transmission to the cloud. Dashboard tool was Grafana which enabled real-time visualization during analysis.[23,24]

Cross-Case Analysis and Industry Benchmarking

By combining findings from multiple implementations with peer-reviewed literature, consistent findings across a range of manufacturing applications emerge regarding the effectiveness of IoT energy monitoring. The observed improvements in energy efficiency are highly demonstrable, as evidenced in both case studies with reductions in energy use of 18-25 % within the documented range presented in the literature.[25] The reduction in maintenance costs of 25 % for steel facility and of 23 % for pharmaceutical facility parallels the 20-30 % reductions documented in the literature. Reduction in downtime for the steel facility was 22 % and for the pharmaceutical facility was 18 %, parallel to downtime reductions of 22-35 % across the cited articles. Payback periods were 7,5 months for the steel facility and 10,1 months for the pharmaceutical facility, both consistent with payback periods from the literature of 8-14 months, confirming the return on investment is consistent across different operational contexts Energy Efficiency Improvements:

Table 5. Energy Efficiency Improvements

Metric	Steel Facility	Pharmaceutical	Literature Range
Energy Reduction	18-22 %	20 %	18-25 %
Maintenance Cost Reduction	25 %	23 %	20-30 %
Downtime Reduction	22 %	18 %	22-35 %
Payback Period	7,5 months	10,1 months	8-14 months

Return on Investment Drivers: the analysis of the components of the return on investment drivers identifies patterns in the costs. The sensors/smart meters cost components represented approximately 32-35 % of the overall implementation costs, and the edge infrastructure/integration was 25-28 %, the cloud platform/analytics were 18-22 %, and the professional services and training were 15-20 %. Facilities with more populations of equipment generally have lower cost for implementation per unit of equipment (0,3-0,5 % of annual energy spend) compared to facilities that fit fall into the definitions of smaller operations (0,8-1,2 % of annual energy spend); this indicates an economic of scale favoring larger comprehensive deployments over the smaller of incremental use cases in the deployment process. This cost structure highlights that as an example facilities should cautiously consider scoping pilot projects so that there is an appropriate scale of application that meets acceptable economics of cost to at least assist with deployment for full deployment.

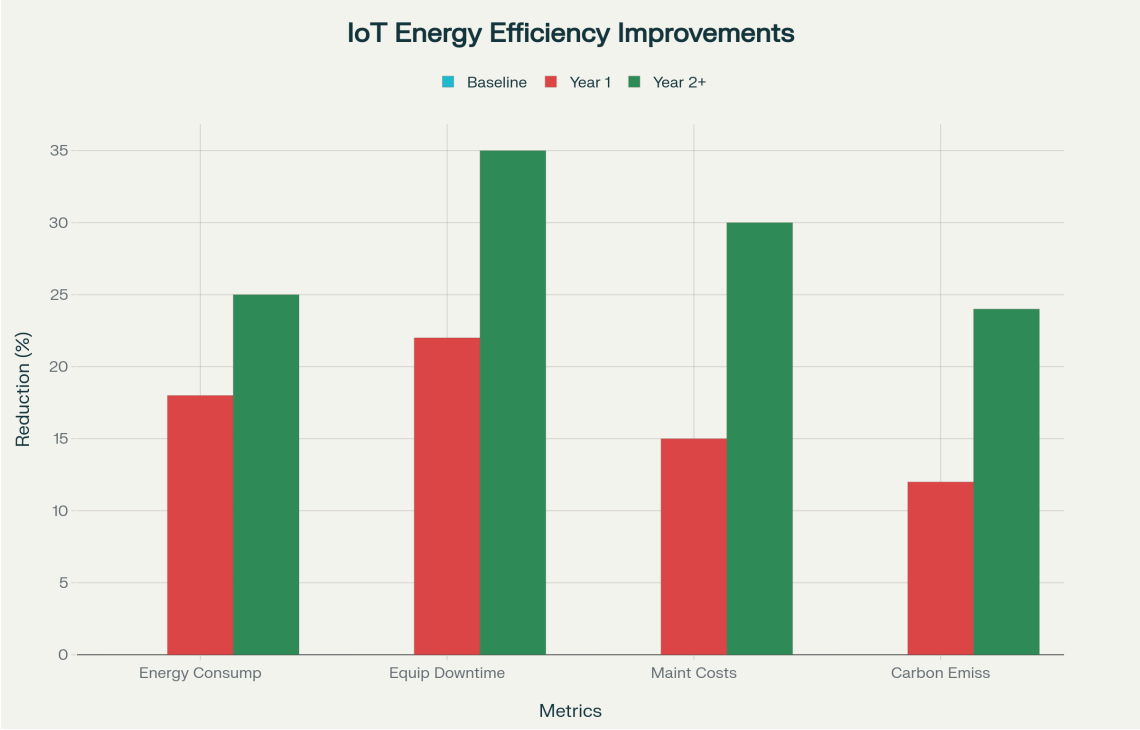


Figure 4. Quantified Benefits of IoT Energy Monitoring Implementation over Time

Digital Twin-Based Optimization

Digital twins produce virtual representations of manufacturing machinery and operations, which allow engineers to evaluate energy savings from optimization rather than stopping production. The integration consists of four primary stages done sequentially and building on prior results. Stage 1 (weeks 1-4) considers model development that involves 1) geometric modeling or CAD conversion of asset layout and representations, 2) physics-based simulation of heat transfer, fluid dynamics, and electrical characteristics, 3) calibrated model parameters to ensure the model is accurate and field data to validate the model. Stage 2 (weeks 5-8) establishes a framework for real-time synchronization. A “real-time” model synchronization has occurred through 1) live data integration, like pulling IoT sensor streams as model inputs, 2) virtual sensors computing parameters not measured, for example, internal bearing temperature with vibration analysis, and 3) a bi-directional feedback element comparing model simulation outputs

with actual values from measurement to detect differences and improve the model. Stage 3 (weeks 9-14) proposes scenario analysis through optimization algorithms (simulated annealing, genetic algorithms) to navigate and evaluate parameter spaces and propose configurations of interest. Constraint programming was introduced to ensure the feasibility of using production schedules and compliance with equipment safety. A sample of a more involved what-if analysis was analyzed for after-the-fact versus top-down analysis - evaluating the results of a process change before implementing it and thereby reducing the risk of field implementation. Stage 4 (ongoing) describes the ongoing implementation of the model based on acceptance of validated recommendations on the production floor and comparison of real-world outcomes with model predictions and subsequent refinement of the model from implementation results.

Challenges and Mitigation Strategies

A key challenge for IoT energy monitoring implementation is the lifetime of manufacturing facilities' equipment averages 15-20 years and must integrate equipment manufactured before the modern standards of communication. There are several mitigation strategies to address this factor across numerous cost-benefit circumstances. Protocol conversion gateways take older protocols (serial Modbus, Profibus, etc.) and convert to modern standards (for example, MQTT, OPC-UA) typically costing between $5000 and $15 000 for each conversion device. Protocol conversion gateways allow integration of equipment without replacing the equipment, making them an option to be adopted for approximately 65 %-70 % of industrial IoT implementations. Sensor retrofit kits typically install modern sensors for place of the legacy system, such as CT/PT combinations with wireless transmitters to replace analog panel meters in legacy systems, typically costing between $1500 and $4000 per piece of equipment, with 2-4 hours of installation time per installation. Middleware platforms service as software layers that will translate between several protocols (some examples are Apache Kafka and AWS IoT Greengrass) while allowing legacy protocol input and modern protocol output (simultaneously).[26] While middleware platforms offer higher complexity than point to point installations, middleware platforms offer greater scalability than point to point methods.

Cost-benefit analyses indicate that retrofit approaches cost 30-50 % less than fully upgrading equipment, while still providing a similar measurement accuracy. Approaches such as these allow organizations to maximize and optimize the integration of legacy systems within a revised budgetary context.

Legacy System Integration

Electrical noise (harmonic distortion, electromagnetic interference), sensor failures, and the resulting data quality issues present significant challenges to industrial environments, necessitating multi-layer validation and mitigative strategies. Multi-layer validation strategies involve immediate range checks and rate-of-change detection at the edge level, cross-correlation analysis and deviation from baseline detection at the cloud level, and quarterly manual spot checks utilizing calibrated reference devices to complement electronic sensors. Sensor redundancy strategies utilize two sensors at key measurement points, generating an alert when the two instruments are not agreeing within a tolerance of 2 %. A second sensor would, thus, provide for continued operation with diminished confidence, or provide for automatic switching to a backup measurement system. Adaptive filtering utilizes Kalman filters and complementary filters to minimize noise while preserving the integrity of the signal. The utilization of these strategies can improve reporting accuracy from +/-2 %-3 % to +/-0,5 %, suitable for more complex analytics/ billing applications.

Table 6. Legacy System Integration Challenges and Mitigation Strategies

Challenge	Impact	Mitigation Strategy	Implementation Cost	Success Rate	Time to Implement
Incompatible Communication Protocols	Cannot connect old equipment to modern IoT systems; requires manual data collection	Deploy protocol adapters/converters (Serial-to-Ethernet, Modbus TCP/IP bridges)	$1500-5000 per device	95 %+	2-8 hours
Lack of Equipment Documentation	Unable to configure sensors or understand equipment capabilities; increases errors	Reverse engineering through testing or request reference manuals from manufacturers	$500-2000 labor cost	85 %	1-4 weeks
Limited Hardware Interfaces	Cannot physically connect new sensors to analog-only equipment	Install Serial-to-Ethernet converters or wireless retrofit kits with data translation	$500-1200 per unit	90 %	4-6 hours
Operational Continuity Requirements	Cannot shut down production for equipment upgrades; business continuity critical	Deploy hot-swap capable hardware; implement changes during planned maintenance windows	$1000-3000 premium for redundancy	80 %	1-2 weeks
Security Concerns with Old Systems	Connecting legacy systems to networks exposes vulnerabilities; compliance risks	Implement air-gapped edge devices; segregate legacy systems on dedicated VLAN; use isolated data bridges	$2000-5000 for secure architecture	100 %	2-4 weeks
Lack of Vendor Support	Manufacturers no longer provide parts or technical support for old equipment	Source compatible third- party components; engage specialist integration partners; implement workarounds	$1000-4000 consulting	75 %	2-6 weeks

Cybersecurity Vulnerabilities

With connected IoT devices being an attack vector to allow unauthorized access, data manipulation, or disruption of operations, security architectures need to be comprehensive. The approach to authentication combines device authentication based on certificates as well as multi-factor user authentication. Data in transit is encrypted using TLS 1.3 while data at rest employs AES-256. Network segmentation identifies VLANs dedicated to energy monitoring, and traffic is restricted to MQTT brokers though firewalls. Suspicious access patterns identified by intrusion detection algorithms trigger alerts, and documented incident response procedures would follow in case of a breach. Research suggests that a comprehensive security implementation can increase costs by 12-18 %, while the cost of a breach is 50-200 times greater due to operational disruption and regulatory fines.

Organizational and Cultural Challenges

Technical capabilities alone are not enough to provide a lasting benefit because staff adoption and integration are needed for successful implementation. Executive sponsorship illustrates

management support for energy optimization, resource allocation, and organizational support. Comprehensive training sets aside 15-20 % of the implementation budget for training that covers system interpretation, organizations workflow of response, and continuous improvements to process. It has been shown that facilities with robust training programs, achieve 20 % more energy savings over their peers with minimal training. Incentive alignment establishes accountability by tying performance metrics to energy efficiency. Transparent communication presents progress, success and challenges while keeping people engaged in the organization.

CONCLUSIONS

Summary of Key Findings

The study demonstrates that IoT-based energy monitoring systems produce significant quantifiable benefits in various manufacturing cases. On the technical side, this includes a demonstrated three-layer architecture (device-edge-cloud) that achieved scalability and resilience, the identification of superior communication protocols (MQTT, OPC-UA, Modbus TCP/IP) enabling interoperability, and confirmed predictive analytics techniques that provided 89-95 % accuracy in energy forecasting and failure forecasting. Validation of implementations through case studies provided evidence of energy savings of 18-25 % compared to 5 % with annual audits, reduction in downtime of 22-35 % with predictive maintenance, reduction in maintenance costs to 20-30 % with condition-based maintenance, and a substantial return on investment through payback periods of 8-14 months. In the case study of a steel facility, the implementation demonstrated savings of 648 000 kWh in the annual period with a payback of 7,5 months, while the case study of a pharmaceutical facility demonstrated savings of 1 024 424 kWh in the annual period with payback of 10,1 months, confirming consistency of benefits across different operational circumstances.

Alignment with Sustainability Goals

The frameworks for energy monitoring proposed by IoT technology enhance various sustainability goals supporting global sustainability commitments. ISO 50001- compliant systems allow for ongoing energy performance monitoring and evidence-based management system documentation, data-driven identification of significant energy uses and opportunities for improvement, and tracking carbon emissions in real-time so as to monitor progress toward a reduction target. The ISO 14001 environmental management standard can integrate supply chain sustainability assessments. Achievement of UN Sustainable Development Goal 7 (Affordable and Clean Energy) will require increased efficiency (18-25 %) which will lead to reduced energy consumption and related cost savings. UN Sustainable Development Goal 9 (Industry, Innovation, Infrastructure) achievement will occur every time supply chain sustainability plans are implemented, thanks to the fulcrum of IoT systems supporting industrial digitalization. UN Sustainable Development Goal 13 (Climate Action) will be addressed in terms of a renewable energy future and supporting reductions of carbon emissions (12-24 %) based on energy efficiency and renewable energy.

Future Research Directions

There are several ways to develop IoT energy management systems that take steps forward. The development of autonomous energy management systems would result in truly autonomous systems which minimize human intervention but still respect safety margins and other business constraints. Integrating multiple energy systems would capture an estimated 30-40 % more optimization than is possible if energy management is focused only on electricity, and thermal, pneumatic, and hydraulic systems are recognized and incorporated into multi-energy system approaches. Blockchain-based energy trading would permit peer-to-peer trading and support

renewable, decentralized energy integration, and demand response, if applicable. Advanced materials and sensor developments can enable lower cost, higher accuracy measurement and provide more comprehensive representation of conditions in more resource-constrained contexts as they develop. Adoption of AI explainability through interpretable models would foster operator trust and help support automated recommendations and possible acceptance of them. Extending current supply chain metrics and carbon accounting is well developed and standards have emerged; expanding the research to consider the energy components of supply chains would result in upstream and downstream carbon footprinting of the facility from the supply chain perspective. The transition of energy management systems in the oil manufacturing sector to a digitally enabled and highly optimized operation is evident in the changes that have taken place at the facility over time. The first manual and instrument-based methods hardly gave a clear view of energy usage, which most of the time led to reactive decision-making and inefficiencies. The use of automation and programmable control systems contributed to the improvement of operational stability; however, they still lacked the analytical depth needed for energy optimization to be done proactively. The deployment of integrated energy management systems was a major step forward as it allowed for the systematic monitoring, data-driven assessment, and coordinated control of the most energy-consuming units such as heaters, compressors, and distillation columns. Currently, intelligent energy management systems, which are based on IoT sensing, real-time analytics, and predictive algorithms, have the capability of consumption forecasting, anomaly detection, and energy flow optimization with an accuracy that has never been attained before. In addition, these developments bring down operational costs and carbon emissions while at the same time increasing equipment safety and making the process more sustainable in the long run. Together, the changeover is a demonstration of how digital technologies are reshaping energy efficiency as one of the essential modern oil manufacturing features.

BIBLIOGRAPHIC REFERENCES

1. Geng D, Evans S, Kishita Y. The identification and classification of energy waste for efficient energy supervision in manufacturing factories. Renew Sustain Energy Rev. 2023;182:113409. https://doi.org/10.1016/J.RSER.2023.113409.

2. Hu Y. Research on Industry 4.0 smart grid monitoring and energy management based on data mining and Internet of Things technology. Therm Sci Eng Prog. 2024;54:102830. https://doi.org/10.1016/J.TSEP.2024.102830.

3. Malek YN, Kharbouch A, El Khoukhi H, Bakhouya M, De Florio V, El Ouadghiri D, et al. On the use of IoT and Big Data Technologies for Real-time Monitoring and Data Processing. Procedia Comput Sci. 2017;113:429–34. https://doi.org/10.1016/J.PROCS.2017.08.281.

4. Zuo Y, Tao F, Nee AYC. An Internet of things and cloud-based approach for energy consumption evaluation and analysis for a product. Int J Comput Integr Manuf. 2018;31:337–48. https://doi.org/10.1080/0951192X.2017.1285429.

5. Khattak YH, Mahmood T, Alam K, Sarwar T, Ullah I, Ullah H. Smart Energy Management System for Utility Source and Photovoltaic Power System Using FPGA and ZigBee. Am J Electr Power Energy Syst. 2014;3(5):86–94. https://doi.org/10.11648/J.EPES.20140305.11.

6. Mensah S. Internet of Things : A Review on Connectivity Gateway Protocols and Semantic Interoperability. In: Proceedings of the 2017 International Conference on Computing and Communication Technologies; 2017.

7. Gautam A. Challenges and Solutions in Implementing Energy-efficient Automation in Smart Buildings. J Environ Eng Stud. 2025;10(2):34–47. https://doi.org/10.46610/JOEES.2025.V010I02.004.

8. Saif S, Wazir S. Performance Analysis of Big Data and Cloud Computing Techniques: A Survey. Procedia Comput Sci. 2018;132:118–27. https://doi.org/10.1016/J.PROCS.2018.05.172.

9. Zare A, Iqbal MT. Low-Cost ESP32, Raspberry Pi, Node-Red, and MQTT protocol based SCADA system. In: 2020 International IOT, Electronics and Mechatronics Conference (IEMTRONICS); 2020. https://doi.org/10.1109/IEMTRONICS51293.2020.9216412.

10. Jasim NA, Salim T, Al Rikabi. Design and Implementation a Smart System for Monitoring the Electrical Energy based on the Internet of Things. Wasit J Eng Sci. 2022;10(2):92–100. https://doi.org/10.31185/EJUOW.VOL10.ISS2.240.

11. Dat MN, Trung KD, Minh PV, Van CD, Tran QT, Ngoc TN. Assessment of Energy Efficiency Using an Energy Monitoring System: A Case Study of a Major Energy-Consuming Enterprise in Vietnam. Energies. 2023;16(13):5214. https://doi.org/10.3390/EN16135214.

12. Akhtar T, Rehman AU, Jamil M, Gilani SO. Impact of an Energy Monitoring System on the Energy Efficiency of an Automobile Factory: A Case Study. Energies. 2020;13(10):2577. https://doi.org/10.3390/EN13102577.

13. Kinnunen H. Cloud Communication of Factory Automation System with OPC UA. In: Proceedings of the 2024 IEEE International Conference on Industrial Technology (ICIT); 2024.

14. Lork C, Choudhary V, Ul Hassan N, Tushar W, Yuen C, Ng BKK, et al. An Ontology-Based Framework for Building Energy Management with IoT. Electronics. 2019;8(5):485. https://doi.org/10.3390/ELECTRONICS8050485.

15. Alex B, Johnson M. A Framework for IoT-Enabled Smart Manufacturing for Energy and Resource Optimization. In: Sustainable Manufacturing in Industry 4.0: Pathways and Practices. Springer; 2025.

16. Gamage KAA, Sajid A, Sonbul OS, Rashid M, Jaffar AY, García-Haro J, et al. A Dynamic Framework for Internet-Based Network Time Protocol. Sensors. 2024;24(2):691. https://doi.org/10.3390/S24020691.

17. Ruddro RA. Energy efficiency monitoring in institutional facilities: a review of UI/UX solutions for IoT dashboards. Int J Sci Interdiscip Res. 2025;6(1):137–62. https://doi.org/10.63125/YHR4G345.

18. Shi Y, Yi C, Chen B, Yang C, Zhu K, Cai J. Joint Online Optimization of Data Sampling Rate and Preprocessing Mode for Edge-Cloud Collaboration-Enabled Industrial IoT. IEEE Internet Things J. 2022;9(18):16402–17. https://doi.org/10.1109/JIOT.2022.3150386.

19. Khasawneh HJ, Al Asbahi R, Alzariqi AW, Al Qada DR, Bujuk A, Nawfal MA, et al. Industrial IoT-based submetering solution for real-time energy monitoring. Discov Internet Things. 2025;5(1):1–16. https://doi.org/10.1007/S43926-025-00110-Y.

20. Roosefert Mohan T, Preetha Roselyn J, Annie Uthra R, Devaraj D, Umachandran K. Intelligent machine learning based total productive maintenance approach for achieving zero downtime in industrial machinery. Comput Ind Eng. 2021;157:107267. https://doi.org/10.1016/J.CIE.2021.107267.

21. Mourtzis D, Angelopoulos J, Panopoulos N. The Future of the Human–Machine Interface (HMI) in Society 5.0. Future Internet. 2023;15(5):162. https://doi.org/10.3390/FI15050162.

22. Jin X, Liu J, Fan W, Sun M, Xiao Z, Fan Z, et al. Research and applications of additive manufacturing in oil and gas extraction and gathering engineering. Materials. 2025;18(14):3353.

23. Omiyale BO, Farayibi PK. Additive manufacturing in the oil and gas industries: A review. Analecta. 2020;14(1):9–18.

24. Shah R, Al-Mansour F, Zubair M. Digital transformation and intelligent automation strategies in upstream oil and gas operations: A comprehensive review. J Pet Sci Eng. 2023;224:111240.

25. El-Hoshoudy AN, Al-Masry W, Abdalla M. Smart polymer systems for enhanced oil recovery: Design principles, performance evaluation, and field potential. Pet Sci. 2022;19(3):1267–84.

26. Saeed M, Khan MJ, Al-Shammari M. Energy-efficient process control and real-time monitoring technologies in the oil and gas sector: Trends and future directions. Energy Rep. 2021;7:5431–45.

FINANCING

None.

CONFLICT OF INTEREST

None.

AUTHORSHIP CONTRIBUTION

Conceptualization: Hariprasad Perumal, Jeevarathinam A, Karan R, Jegan Karthik S, Gokulnath P, Prabhu P, Malikov Ziyodullo Abdurayim.

Data curation: Hariprasad Perumal, Jeevarathinam A, Karan R, Jegan Karthik S, Gokulnath P, Prabhu P, Malikov Ziyodullo Abdurayim.

Formal analysis: Hariprasad Perumal, Jeevarathinam A, Karan R, Jegan Karthik S, Gokulnath P, Prabhu P, Malikov Ziyodullo Abdurayim.

Drafting - original draft: Hariprasad Perumal, Jeevarathinam A, Karan R, Jegan Karthik S, Gokulnath P, Prabhu P, Malikov Ziyodullo Abdurayim.

Writing - proofreading and editing: Hariprasad Perumal, Jeevarathinam A, Karan R, Jegan Karthik S, Gokulnath P, Prabhu P, Malikov Ziyodullo Abdurayim.