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Real Time Industrial Energy Monitoring Using IoT and Edge Computing for Sustainability and Carbon Tracking

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Abstract

Global energy consumption has increased rapidly in recent decades due to industrial growth and expanding infrastructure, contributing to rising greenhouse gas emissions and climate change. However, many small and medium-sized industries still rely mainly on monthly electricity bills to monitor their energy usage, which provides delayed information but also makes it difficult to identify and correct energy inefficiencies in real time. This paper presents the design and implementation of **AeiX**, an IoT-based real-time energy monitoring system that integrates energy meters, sensors, edge computing, and cloud analytics to provide continuous visibility into industrial energy consumption. The system uses ESP32-based monitoring nodes equipped with voltage and current sensors to measure electrical parameters. Data is transmitted through the MQTT communication protocol to a time-series database (InfluxDB) and visualized using Grafana dashboards. A second prototype extends the system for industrial deployment using a Raspberry Pi connected to Modbus-enabled digital energy meters. A carbon analysis module converts energy data into estimated CO_2 emissions using standard grid emission factors. A pilot deployment in an industrial facility monitored energy for two weeks. It identified hidden nighttime compressor loads, leading to a 7.5% reduction in nighttime electricity consumption after corrective action. It also detected a malfunctioning capacitor panel through abnormal power factor readings, improving the power factor from 0.2 to 0.95 after repair. This study demonstrates how a low-cost IoT monitoring platform can transform raw energy data into actionable sustainability insights. Continuous measurements and dashboard-based visualization enables industries to identify inefficiencies and take timely actions that improve energy efficiency and sustainability. The architecture provides a scalable framework for future integration with predictive analytics and carbon accounting systems, supporting progress toward Net-Zero targets and UN Sustainable Development Goal 12: Responsible Production and Consumption.

Keywords
Industrial IoT, Energy Monitoring, Smart Manufacturing, Carbon Tracking, Sustainable Energy Systems

1. Introduction:
Over the last few decades, global energy consumption has risen significantly due to factors such as rapid industrialization and economic growth. This increased demand for energy has contributed to rising greenhouse gas emissions and climate change resulting in governments and international organizations promoting strategies which aim at achieving the Net-Zero emissions goal by 2050.

Industrial facilities are amongst the biggest consumers of electricity, and improving the energy efficiency within these industrial operations is a major and important step towards reducing the global carbon emissions. Though most of these industrial organizations still rely on traditional energy monitoring practices which involve use of manual meter readings and monthly utility bills. The major issue with these methods is that they are only able to provide a limited insight into energy consumption patterns and are unable to provide organizations with the ability to detect any inefficiencies in real-time.

Advancements in Internet of Things (IoT) technologies are able to provide new opportunities to monitor and understand energy consumption patterns through continuous monitoring with the help of distributed sensors and connected data platforms. IoT-enabled energy monitoring systems can accurately collect electrical measurements, transmit data through communications

This research brings forth the design and the implementation of AeiX, an IoT-based energy monitoring system with the goal to provide real-time visibility into industrial energy consumption. The module incorporates edge computing devices, sensor nodes, and cloud-based analytics platforms, with the goal to collect, process, and visualize energy data.

The objective of this research is to demonstrate how real-time monitoring systems can help organizations identify hidden energy inefficiencies and support data-driven sustainability initiatives.

1.1 Objectives

To design a real-time industrial energy monitoring system using IoT sensor nodes and edge computing.
Design a Centralized Data Management and Visualization Platform
Build a centralized time-series infrastructure using InfluxDB for data storage and Grafana for real-time visualization.
Create an interactive Grafana-based web dashboard that displays energy usage, source comparison, and carbon footprint metrics.
To demonstrate the practical deployment of a low cost monitoring system in an industrial environment.
To evaluate the system's ability to identify hidden energy inefficiencies and improve energy performance
To quantify measurable energy savings
To translate energy data into estimated CO_2 emissions for sustainability reporting
Quantify and Display Sustainability Indicators
Calculate carbon emissions, energy efficiency scores, and basic sustainability indicators.
Translate raw energy data into meaningful sustainability insights for decision-makers.
Support **Data-Driven Action Toward Net-Zero Goals**
Empower industries to track, compare, and optimize their energy footprint dynamically.
Create groundwork for **Analysis and Future Optimization**
Structure the collected time-series data so that machine learning algorithms can be applied in future to identify consumption patterns and predict energy demand trends.

This paper makes the following contributions:
Development of a low-cost, real-time industrial energy monitoring system using IoT and edge computing.
Demonstration of a scalable architecture integrating sensing, communication, data storage, and visualization.
Experimental validation through industrial deployment, achieving measurable energy savings of 7.5%.
Integration of carbon emissions estimation with real-time monitoring for sustainability analysis.
Outline of a planned future-ready framework toward MRV-compatible carbon credit accounting workflow, including blockchain-based audit layer described as future work.

2. Literature Review

2.1 Industrial Energy Monitoring

Recent research has explored the use of IoT technologies to improve energy monitoring in industrial environments. With advances in embedded systems and wireless communication, modern energy monitoring systems now use distributed sensor networks to capture real-time operational data. Mekhilef et al. (2022) highlighted that digital monitoring platforms can significantly improve energy efficiency by providing more granular visibility into energy consumption patterns.

However, many industrial facilities still rely on traditional monitoring methods such as manual meter readings and monthly electricity bills. These approaches provide only limited insight into energy usage and are not capable of identifying short-term inefficiencies or abnormal load behavior. This creates a need for systems that can provide continuous and real-time monitoring of energy consumption.

2.2 IoT-Based Energy Management Systems
IoT-based energy monitoring platforms have been widely proposed for smart factories and industrial environments. Kumar and Prakash (2015) developed an IoT-based energy management system using sensor networks and cloud computing to track electrical parameters in real time. Similarly,Viswanathan (2018) demonstrated that IoT-based energy monitoring architectures using embedded computing and sensor integration can provide a cost-effective framework for real-time industrial energy monitoring and visualization.

These systems enable automated data collection, remote visualization, and basic anomaly detection. Energy Management Systems (EMS) are increasingly being adopted to optimize power consumption in large-scale industries. The International Research Journal of Engineering and Technology (IRJET) (2016) analyzed EMS adoption challenges in India, including high upfront costs, limited technical expertise, long payback periods, and variable energy tariffs. The study emphasized that IoT-based systems can reduce these barriers by automating data collection, visualization, and reporting.

In addition, the Bureau of Energy Efficiency (BEE) (2021) has introduced guidelines to promote structured energy monitoring and auditing practices in industries. These policies encourage the adoption of digital energy monitoring systems and standardized reporting frameworks.

2.3 AI and Smart Energy Optimization
Artificial intelligence techniques are increasingly used to optimize industrial energy consumption. Mishra and Soni (2020) showed that AI-enabled energy management systems can improve industrial energy efficiency by up to 18% through predictive maintenance and load forecasting.
Such systems combine machine learning algorithms with IoT sensor data to identify patterns in energy consumption and recommend operational improvements. However, the effectiveness of these approaches depends on the availability of reliable, high-frequency data, which is often not available in traditional monitoring systems.

2.4 Carbon Accounting and Sustainability Monitoring
With increasing global focus on climate change, carbon accounting has become an important component of energy monitoring systems. The United Nations Net-Zero Coalition (2023) emphasizes the need for transparent and verifiable data on energy use and emissions to ensure accountability in sustainability reporting.
Hickel (2019) discusses the global imbalance in energy consumption and highlights the need for both technological innovation and behavioral change to achieve sustainable development. This includes improving energy efficiency, integrating renewable energy sources, and enabling better transparency in energy usage.
Recent studies have also explored the use of blockchain-based systems for carbon tracking and verification. Kumar and Shukla (2022) proposed data-driven approaches for enabling transparent carbon accounting systems. These systems support Monitoring, Reporting, and Verification (MRV) frameworks required for carbon credit mechanisms.

2.5 Research Gap
Despite these advancements, several limitations remain in existing energy monitoring systems. Many solutions are either expensive, complex to deploy, or designed primarily for large-scale industrial applications. As a result, small and medium-sized industries still lack access to affordable and scalable real-time monitoring systems.

In addition, most existing systems do not fully integrate real-time energy monitoring with carbon emissions estimation and sustainability tracking within a single platform.

This study addresses these gaps by developing a low-cost, scalable IoT-based monitoring system that combines real-time data acquisition, edge computing, cloud analytics, and carbon tracking. The proposed system aims to provide practical and actionable insights for improving energy efficiency and supporting sustainability goals in industrial environments.

Table 1. Research Gap Comparison

Feature	Kumar & Prakash 2015	Viswanathan 2018	Mishra & Soni 2020	AeiX (this work)
Real-time monitoring	Yes	Yes	Yes	Yes
Edge computing	No	Yes	No	Yes
Modbus industrial integration	No	No	No	Yes
Carbon emissions estimation	No	No	No	Yes
SME-affordable cost	Partial	Yes	No	Yes
Industrial pilot validation	No	Partial	Simulation	Yes

3. Methods

3.1 System Architecture

The AeiX architecture consists of **six functional layers**:

Table 2. System Architecture

Layer	Function
Physical sensing layer	Modbus based Multi function meters (MFM), sensors to measure voltage and current
Edge computing layer	Raspberry Pi 4
Communication layer	MQTT protocol transmits sensor data and Modbus data from MFM
Data platform layer	MQTT data is time stamped using telegraf and then stored in InfluxDB as time-series energy data. Packets are hashed for data integrity and future auditability through possible blockchain-supported MRV workflows
Application layer	Grafana dashboards visualize energy metrics, Alerts generation for anomaly detection, carbon metrics (CO_2 avoidance and CO_2 emissions)
Audit Layer (under development)	Blockchain-based audit support for future MRV workflows

The study was conducted in two phases to validate the system architecture.

3.2 Prototype 1: Laboratory Implementation

Phase 1:

A laboratory-scale prototype was developed using an ESP32-based energy monitoring node. The system measures voltage and current using ZMPT101B and SCT-013 sensors. The microcontroller computes electrical power and transmits the data to a cloud platform for real-time visualization.

Circuit Diagram :

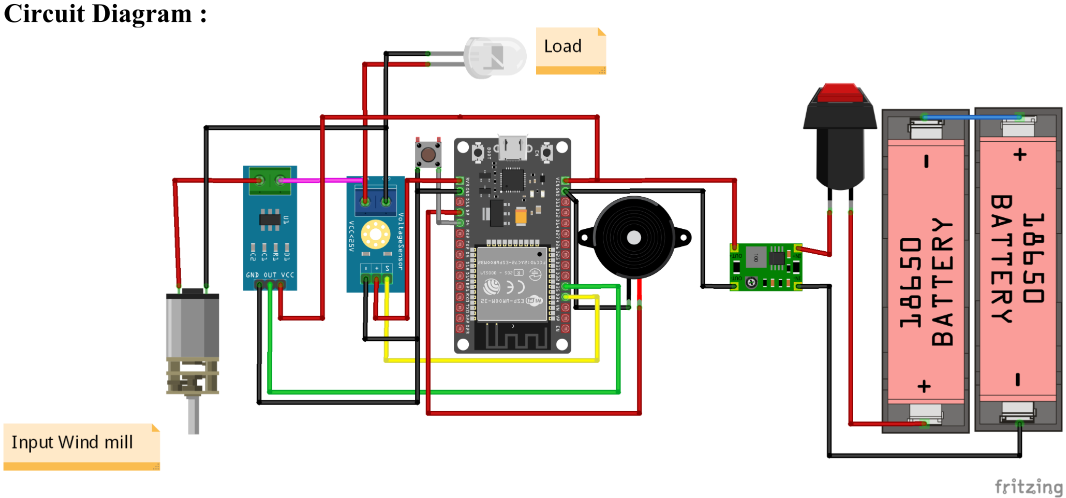

Figure 1: Circuit diagram of ESP32-based laboratory prototype

3.3 Pilot Implementation (Phase 2: Industrial Deployment)

Phase 2:

The pilot implementation focuses on developing an advanced industrial energy monitoring and verification system aligned with the AeiX multi-layer architecture. The system integrates Raspberry Pi–based edge computing, Modbus communication, and an open-source time-series data stack to enable real-time monitoring and analytics.

At the physical sensing layer, data is collected from Modbus-enabled multifunction energy meters (MFMs) and sensors measuring electrical parameters such as voltage and current. This data is acquired through Modbus RTU communication.

At the edge computing layer, a Raspberry Pi acts as the gateway device, interfacing with industrial meters and sensors. It collects raw data and prepares it for transmission.

At the communication layer, data is transmitted using the MQTT protocol via a Mosquitto broker. Sensor and meter readings are published as structured JSON payloads to defined MQTT topics, enabling scalable and reliable data transfer.

At the data platform layer, Telegraf is used to ingest MQTT data, apply timestamping, and forward it to InfluxDB, where it is stored as time-series energy data. To support future auditability, data packets are hashed, enabling later anchoring onto a blockchain or distributed ledger for tamper-evident storage and future MRV-compatible carbon accounting applications.

At the application layer, Grafana Dashboards are used to process and visualise the incoming data to compute energy consumption, efficiency indicators, and estimated carbon emissions. This provides real-time insights into power usage, renewable versus non-renewable energy contributions, and sustainability metrics. Alerting mechanisms are implemented to detect anomalies and threshold violations.

An audit layer (under development) is designed to integrate blockchain technologies such as Hyperledger, enabling secure carbon tracking, monitoring, reporting, and verification (MRV) in the future.

3.4 System Implementation Steps

System Setup and Hardware Configuration

Industrial machines, test loads, and energy meters are connected via Modbus RTU. The Raspberry Pi is configured as a Modbus master to read electrical parameters such as voltage, current, and power factor. The device is connected to a local network to enable communication.

Data Transmission via MQTT
The Mosquitto MQTT broker is installed and configured on the Raspberry Pi. Sensor and meter readings are published as JSON payloads to predefined MQTT topics. Data transmission is verified through subscription and monitoring of topics in real time.

Data Storage and Processing
Telegraf is deployed to subscribe to MQTT topics, timestamp incoming data, and forward it to InfluxDB. A structured schema is defined in InfluxDB for parameters such as voltage, current, kW, kVA, and power factor. A Python-based Carbon Analyzer processes the data to estimate carbon emissions and evaluate energy efficiency.
Visualization and Analytics

Grafana is configured to connect with InfluxDB for real-time visualization. Dashboards are developed to display energy consumption, carbon emissions, and system performance metrics. Alerting mechanisms are enabled to identify abnormal load behavior and threshold breaches.

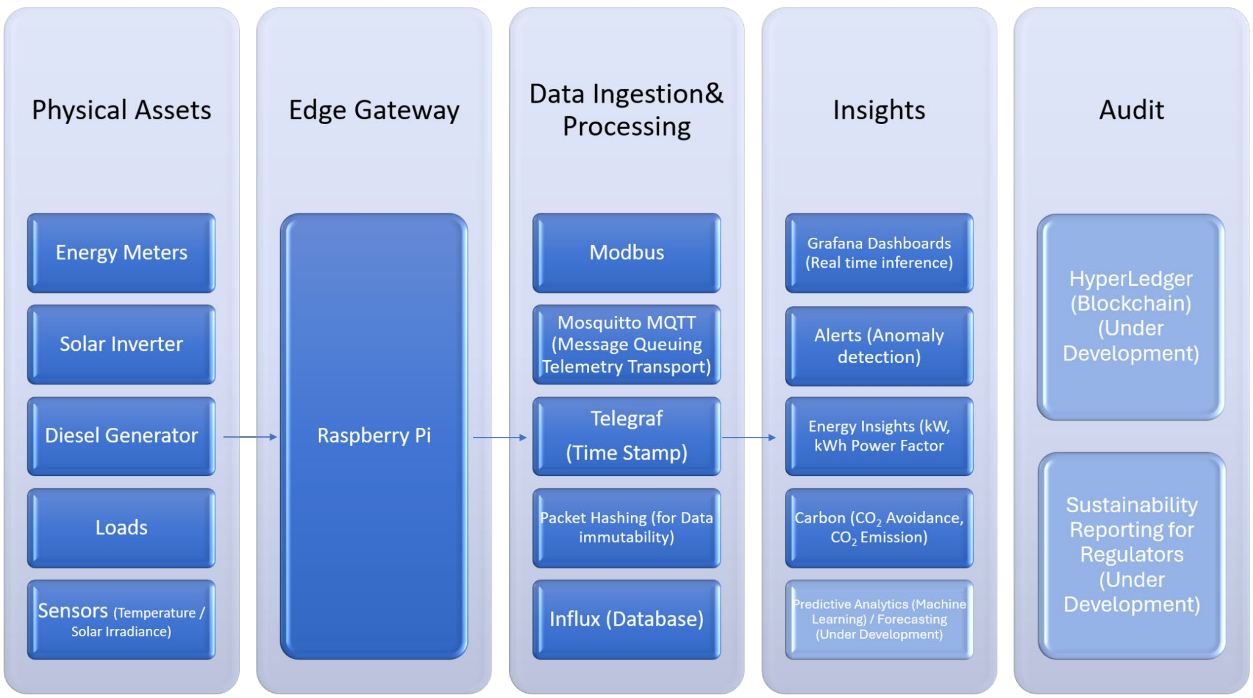

Figure 2: System Architecture

3.5 Mathematical Modelling

Power Calculation:

$$P = V \times I \qquad (1)$$

Energy consumption:

$$E = \int P dt \qquad (2)$$

Carbon Emissions Estimation Model
Carbon emissions from electricity consumption were estimated using:

$$CO_2 = E \times EF \qquad (3)$$

Where: E = energy consumption (kWh)
EF = emission factor (kg CO_2/kWh)
For India: $EF \approx 0.82\ kg\ CO_2/kWh$

The system provides measurement data that could, in future work, support MRV workflows. Generation of tradable credits would require baseline definition, additionality analysis and third-party verification under standards such as Verra, the Gold Standard or CDM — not implemented in the present system. To ensure data integrity, energy records are hashed and can be anchored onto a blockchain-based system such as Hyperledger. This enables the creation of tamper-evident data logs that can support Monitoring, Reporting, and Verification (MRV) requirements.

4. Data Collection

Data for this study was collected through two experimental setups: a laboratory prototype and an industrial pilot deployment.

In the laboratory **environment**, an ESP32-based energy monitoring node measured voltage and current signals using ZMPT101B voltage sensors and SCT-013 current sensors. The system computed electrical power using embedded microcontroller algorithms. Measurements were sampled at 5-second intervals and transmitted to a cloud platform for real-time visualization.

In the **industrial pilot deployment**, data was collected from Modbus-enabled digital multifunction energy meters connected to a Raspberry Pi gateway. The system recorded key electrical parameters including voltage, current, power factor, real power (kW), and apparent power (kVA).

Table 3: Data collection parameters

Parameter	**Value**
Monitoring duration	14 days
Sampling interval	5 seconds
Total data points collected	~240,000
Number of monitored loads	3
Data storage platform	InfluxDB
Visualization tool	Grafana
Dashboard latency	<2 seconds
Energy anomaly detection	successful
Energy savings	7.5%

Table 4: Comparison with existing energy monitoring systems

Feature	Traditional Systems	Proposed AeiX System
Monitoring frequency	Monthly	Real-time
Data integration	Manual	Automated
Energy anomaly detection	No	Yes
Carbon emissions estimation	No	Yes

Cost	High	Low

5. Results and Discussion

5.1 Numerical Results

During the pilot deployment, the system identified abnormal periodic spikes in nighttime energy consumption. These spikes were traced to the automatic operation of an air compressor that was refilling air at regular hourly intervals.

By sequentially isolating different electrical loads, the source of the inefficiency was identified. After disabling the unnecessary compressor operation during non-production hours, a measurable reduction in energy consumption was observed.

Table 5: Energy consumption before and after intervention

Metric	Before	After
Night Energy Consumption	21.5 kWh	20 kWh
Energy Savings	-	1.5 kWh
Percentage reduction	-	7.5%

This demonstrates the effectiveness of real-time monitoring in identifying hidden inefficiencies that are not visible through conventional monthly billing systems.

Algorithm: Energy Anomaly Detection
1. Collect real-time power measurements P(t)P(t)P(t)
2. Compute moving average power consumption
3. Define threshold based on baseline behavior
4. Identify deviations exceeding the threshold
5. Flag abnormal loads

Trigger alerts on the dashboard

Energy Consumption Analysis

A comparative analysis was conducted to evaluate energy consumption before and after system intervention. The system successfully identified abnormal nighttime loads, leading to corrective actions and measurable energy savings.

Performance Evaluation

The system demonstrated strong performance in real-time monitoring and anomaly detection. A reduction of **7.5% in energy consumption** was achieved after identifying and eliminating inefficient load behavior.

5.2 Graphical Results

Energy consumption patterns were visualized using Grafana dashboards. The initial data showed clear periodic spikes in electricity usage during nighttime operation. After corrective actions were implemented, these spikes were eliminated, resulting in a smoother and more stable energy consumption profile.

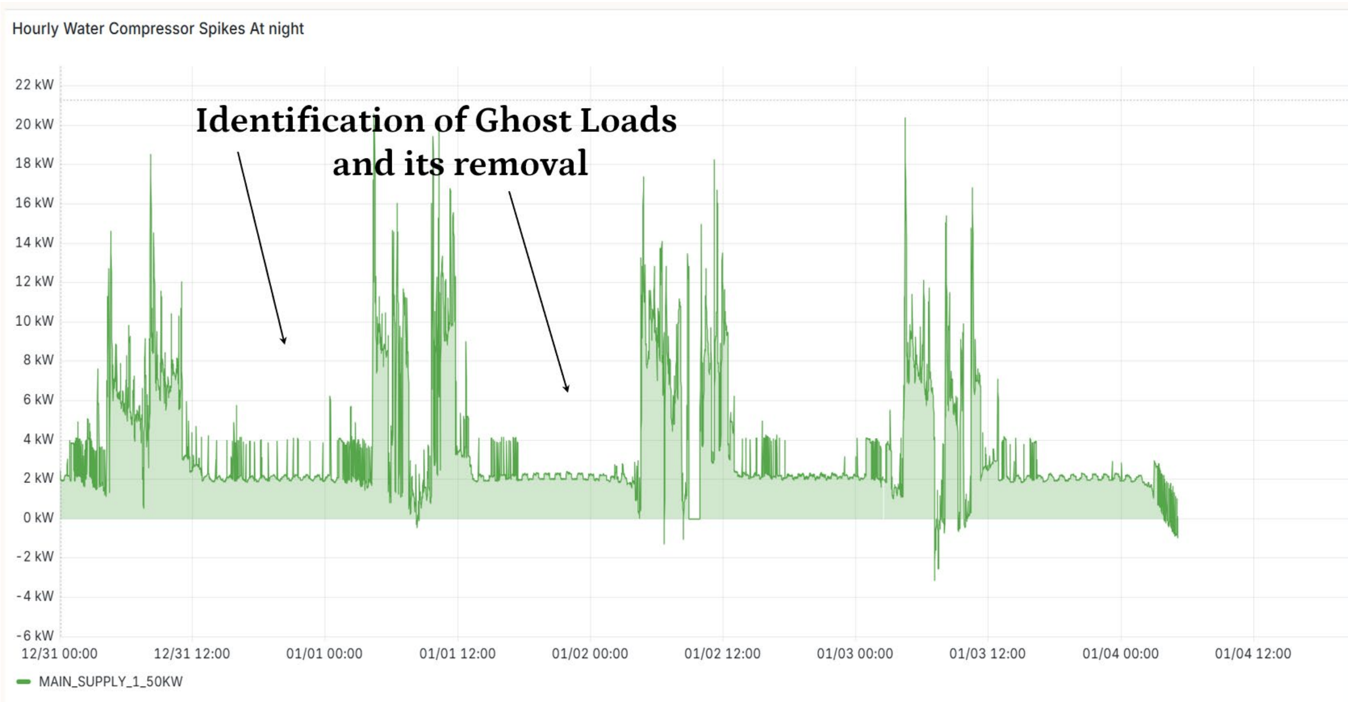

Figure 3: Energy consumption before and after intervention

In addition, the system detected abnormal power factor readings associated with a malfunctioning capacitor panel. After repair, the power factor improved significantly from 0.2 to 0.95.

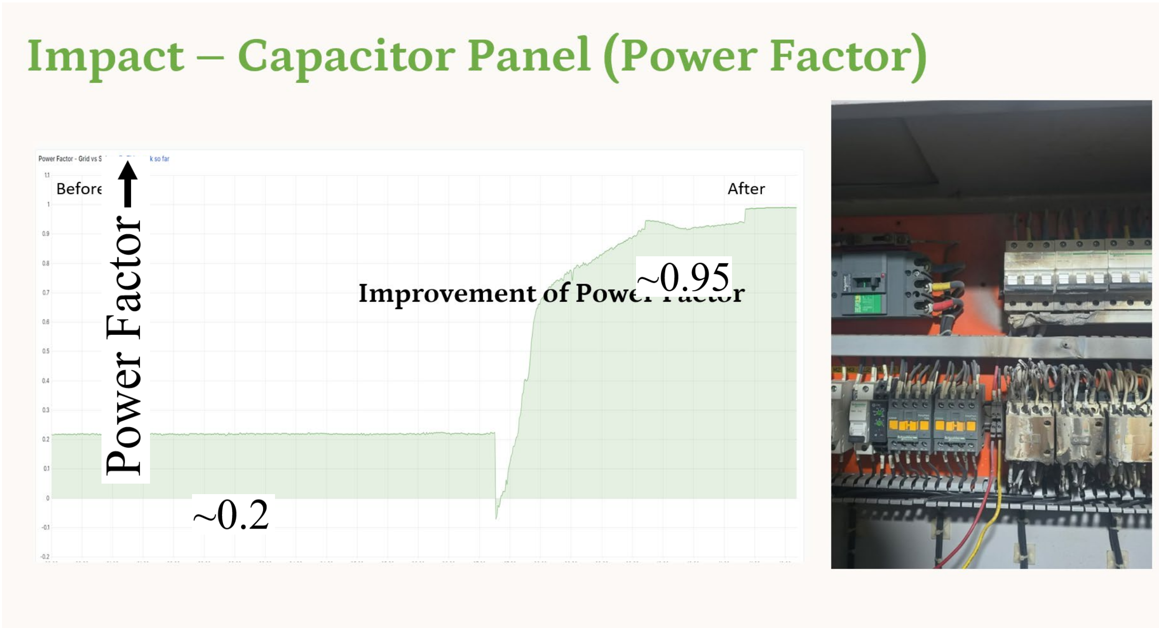

Figure 4: Power factor improvement after capacitor panel correction

These graphical results validate the system's ability to detect inefficiencies and support corrective actions in real time.

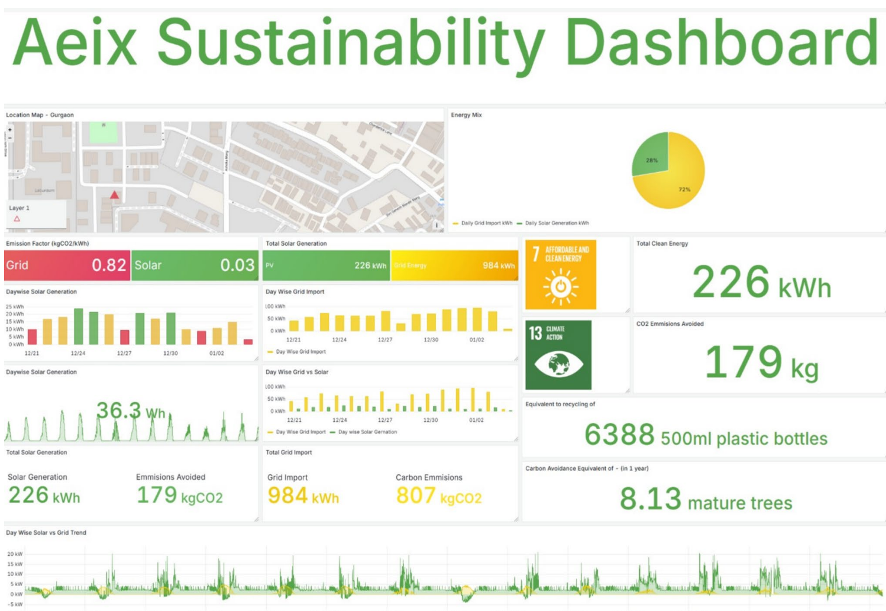

Figure 5: Grafana Sustainability Dashboard

Figure 6: Energy From Solar and Grid

Control and Feedback Mechanism

1. Integrate GPIO and Modbus outputs on the Raspberry Pi to send control signals back to relays or PLCs.
2. Future versions of the system may automate decisions such as switching between grid and solar sources based on energy efficiency and demand. This functionality was not implemented or experimentally validated in the present study.

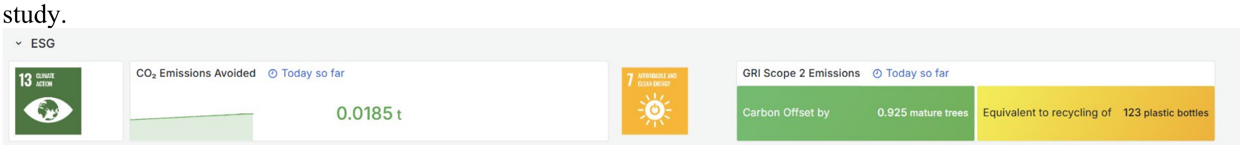

Figure 7: Emission Result

Figure 8: Solar energy Graphs

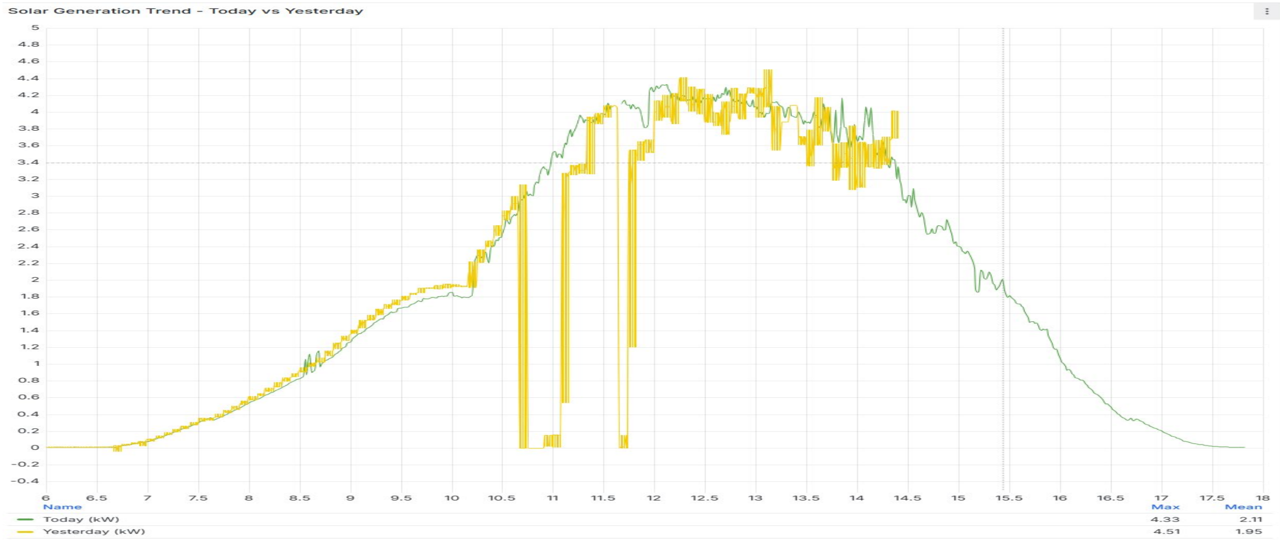

Figure 9: Solar Generation Trend

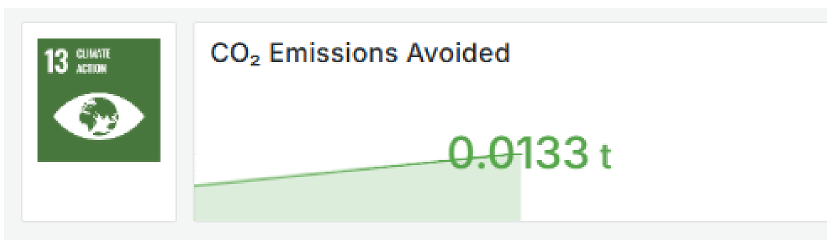

Figure 10. CO_2 Emissions

5.3 Proposed Improvements

The monitoring system can be extended to support advanced analytics, including:

1. machine learning-based demand forecasting
2. tariff-aware load optimization
3. predictive maintenance for industrial equipment

These capabilities would enable automated decision-making for energy optimization.

5.4 Validation and Statistical Analysis

To evaluate system accuracy, measurements recorded by AeiX were compared with readings obtained directly from industrial energy meters.

Table 6: Measurement validation

Measurement	Meter	AeiX	Error
Voltage	230V	228V	0.9%
Current	4.51A	4.60A	2.0%
Power	1.05 kW	1.03 kW	1.9%

The percentage error was calculated using:

$$Error\ (\%) = \frac{|Measured - Actual|}{Actual} \times 100$$

The mean error across all measured parameters was 1.6%, with the largest individual error being 2.0%, indicating that the system provides sufficiently accurate measurements for industrial monitoring applications.

To further assess system consistency, repeated measurements were analyzed over the monitoring period. The standard deviation of the recorded values remained low, indicating stable and reliable sensor performance.

Validation statistics were computed using approximately 15 synchronized observations collected over three operating cycles during the monitoring period across representative operating conditions.

The Mean Absolute Error (MAE) across all measured parameters was 1.6%, with no individual parameter exceeding 2.0% error, indicating high measurement accuracy. The low variance in repeated measurements confirms the stability and reliability of the sensing system over continuous operation.

These results confirm that the proposed system achieves acceptable accuracy levels comparable to commercial monitoring systems, while maintaining a low-cost and scalable architecture.

5.5 Statistical and Comparative Analysis

To further evaluate system performance, key statistical indicators were considered:

1. Mean Absolute Error (MAE): Measures average deviation between measured and actual values
2. Percentage Error: Indicates relative measurement accuracy
3. Response Latency: Measures delay between data acquisition and visualization

Table 7: System performance metrics

Metric	Value
Data latency	2 seconds
Measurement error	≤2.0% (MAE ≈1.6%)
Energy savings detected	7.5%
Power factor improvement	0.2 → 0.95

These results indicate that the system is capable of real-time monitoring with high reliability and low latency.

5.6 Limitations

Although the system demonstrates successful energy monitoring, several limitations remain. The current study involves a limited number of sensors and a single industrial pilot deployment. Larger-scale deployments across multiple facilities are required to validate the scalability and robustness of the system.

5.7 Discussion

The results of this study demonstrate that real-time energy monitoring can reveal hidden energy inefficiencies that are not visible through monthly electricity bills. During the Terra Tech pilot trial, the system detected periodic spikes in electricity consumption during the night caused by compressors operating automatically. Eliminating this unnecessary load reduced nighttime electricity consumption by 7.5%. The platform also identified malfunctioning capacitor panels through analysis of kWh consumption patterns and power factor readings. After repair of the capacitor panel, the power factor improved from 0.2 to 0.95, eliminating utility penalty charges and improving overall power quality.

Through the development of two prototypes, this project achieves a practical, scalable approach for real-time energy management. The end-to-end delay from measurement to dashboard was consistently under two seconds, enabling real-time monitoring and pattern recognition.

These observations indicate that real-time monitoring brings in enhanced visibility of electricity production and consumption. It also helps in patterns in energy usage, such as unusual spikes or readings that are not expected. By providing continuous measurements and dashboard based visualisation of energy consumption data, the system enables factories to identify abnormal load behaviour and respond quickly to equipment faults.

The system demonstrates the ability to convert raw energy data into actionable insights, enabling data-driven decision-making for industrial energy optimization.

The integration of real-time monitoring with carbon estimation may support future assessment of emissions reduction opportunities and sustainability reporting. By accurately measuring reductions in energy consumption, the system enables quantification of avoided CO_2 emissions.

For example, a 7.5% reduction in nighttime energy consumption directly translates into a proportional reduction in carbon emissions. When combined with verifiable data logging and audit mechanisms, such reductions could, in future work, be paired with formal MRV and third-party verification. This highlights the potential of the system as an energy-monitoring and emissions-estimation tool, with sustainability-reporting and carbon-credit workflows identified as a future extension.

The findings demonstrate that low-cost IoT-based systems can deliver measurable industrial impact while also enabling carbon accountability. By combining real-time monitoring with carbon estimation and future-ready audit mechanisms, the proposed system bridges the gap between energy management and sustainability reporting. This positions the platform as not only a technical solution but also a strategic tool for industries transitioning toward data-driven and carbon-aware operations.

Table 8: System Impact Summary

Metric	**Before**	**After**	**Improvement**
Energy Consumption	21.5 kWh	20 kWh	↓ 7.5%
Power Factor	0.2	0.95	Significant
Monitoring Method	Manual	Real-time	Improved
Response Time	N/A	<2 sec	Real-time

The results highlight a key insight: many industrial inefficiencies are not due to large system failures but due to small, recurring operational behaviors that remain undetected in traditional monitoring systems. The ability of the proposed system to identify such hidden loads demonstrates the importance of high-resolution, real-time data in industrial energy optimization. This shifts energy management from reactive analysis to proactive decision-making.

6. Conclusion

This study demonstrates the development of a practical IoT-based energy monitoring system that integrates sensor nodes, edge computing and a time-series data platform for real-time energy analysis. Two prototypes were developed and tested, showing a scalable approach for monitoring electrical loads in both laboratory and factory environments.

By automating data collection and analysis, the platform provides accurate and continuous insights into energy use that are not available through conventional monitoring methods such as monthly electricity bills.
Overall, the prototypes establish a strong foundation for the development of more advanced Energy Management Systems (EMS) that can support energy efficiency improvements, renewable energy integration and monitoring of carbon emissions.

Machine learning–based optimization, automated control, blockchain auditability, and MRV-compatible carbon accounting remain future development directions and were not experimentally validated in this study.

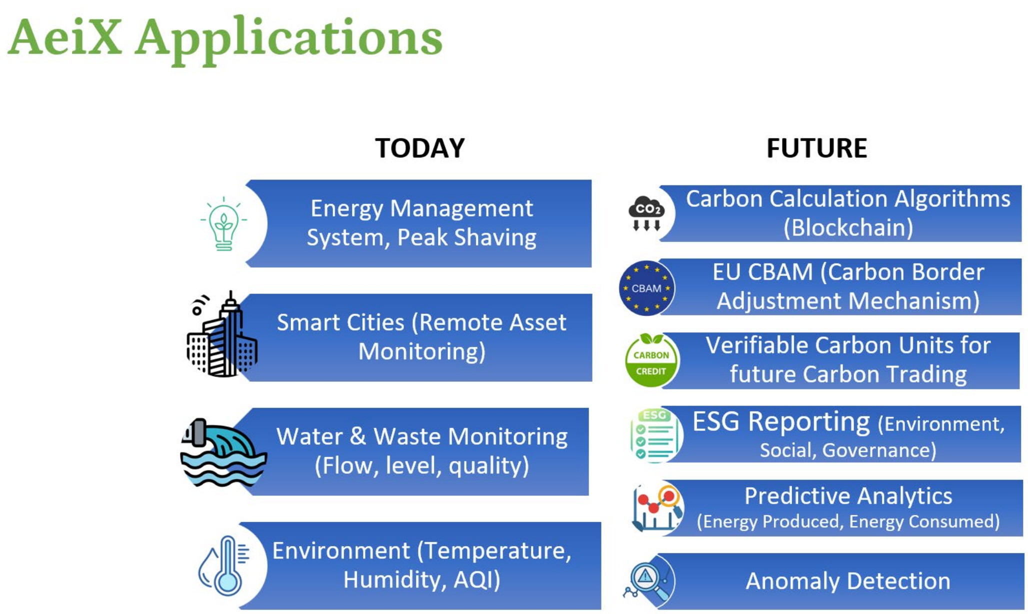

Figure 11. Application Areas

Applications

Carbon emissions tracking:
Energy consumption data collected by the system can be converted into estimated CO_2 emissions using standard grid emission factors. This allows organisations to monitor emissions reductions resulting from efficiency improvements or increased use of renewable energy sources.

Operational efficiency:
Continuous monitoring enables early detection of abnormal load behaviour and equipment faults, supporting predictive maintenance and reducing operational inefficiencies.

Sustainability awareness:
Real-time dashboards displaying energy use and carbon metrics can help organisations better understand the environmental impact of their operations. This supports responsible energy management practices and contributes to **UN Sustainable Development Goal 12: Responsible Production and Consumption**.

Future Work

Future development of the AeiX platform will focus on advanced analytics and demand-side optimisation. The system can be extended by adding a Python-based module for carbon and tariff analysis. The data model is also designed so that batches of energy records can later be anchored on a blockchain or similar distributed ledger to support tamper-evident ESG reporting. Preliminary what-if analysis suggests that shifting flexible industrial loads away from peak tariff periods could reduce grid energy consumption during high-price windows by approximately 5–10%. However, this capability has not yet been experimentally implemented or validated in the current phase of the project.

The framework can also be extended to support ESG reporting and carbon accounting by integrating automated carbon calculation modules. This system can be further developed to support advanced analytics, demand forecasting, and optimisation of industrial energy usage, especially for small and medium-sized businesses and factories.

Future work will focus on:

1. machine learning for energy prediction
2. automatic load optimization
3. carbon accounting for supply chains
4. blockchain-based carbon verification

References

Bureau of Energy Efficiency. Energy Efficiency in Industry: Policy Framework and Guidelines. Government of India, Ministry of Power, 2021. Retrieved from https://beeindia.gov.in

Gavate, C., Ingale, S., Joshi, Y., Phase, S., & Rao, P. N. Industrial Power Monitoring and Load Controlling System. *MDPI Sustainability Journal*, 15(11), 8788, 2016.

Hickel, J. *There Is No Planet B: A Handbook for the Make or Break Years*. London: Penguin Books, 2019.

International Journal of Research in Technical Innovation (IJRTI), 2018.

International Research Journal of Engineering and Technology (IRJET). Energy Management Systems: Integrated Control and Monitoring for Industrial Operations, 2016. Retrieved from https://www.irjet.net/archives/V3/i11/IRJET-V3I1149.pdf

Kumar, R., & Shukla, A. Blockchain and Data-Driven Approaches for National Net-Zero Pathways. *Energy Policy*, 160, 112678, 2022.

Kumar, S. P., & Prakash, S. IoT-Based Energy Management Systems for Industrial Applications. *International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering*, 4(7), 56–64, 2015. Retrieved from https://www.ijareeie.com/upload/2015/july/111A_S.PRAKASH_3.pdf

Mekhilef, S., Safari, A., & Saidur, R. Energy Consumption, Emissions, and Climate Change: Global Perspectives. *Journal of Cleaner Production*, 378, 134580, 2022. Retrieved from https://www.sciencedirect.com/science/article/abs/pii/S2352710222011482

Mishra, R., & Soni, A. AI-Enabled Energy Management Systems for Industrial Optimization. *Journal of Cleaner Production*, 261, 121220, 2020.

United Nations. Net-Zero Coalition: Climate Action for a Sustainable Future. United Nations Climate Action Portal, 2023. Retrieved from https://www.un.org/en/climatechange/net-zero-coalition

Viswanathan, K. IoT-Based Energy Footprint Monitoring Using Raspberry Pi and Sensors, 2018. Retrieved from https://ijrti.org/papers/IJRTI1812005.pdf

Biography

Aditya Krishan Goel is a high school researcher and innovator at The Shri Ram School, Aravali, India. His work focuses on creating IOT based intelligent energy systems for sustainable usage. He founded AeiX, an industrial sustainability platform designed to help small & medium-sized enterprises monitor energy consumption, identify inefficiencies, and reduce carbon emissions through data-driven dashboards and analytics. He was selected as a Finalist at the IRIS National Science Fair (Regeneron ISEF affiliated) for his project on sustainable energy systems aligned with UN Sustainable Development Goal 12: Responsible Consumption and Production. He also won Sigma XI 2026 Student Research Showcase Interdisciplinary Award in Engineering Category for research on IoT-based Industrial Energy Monitoring & Carbon Visibility. He authored a research paper titled *AI and Machine Learning Driven Intelligent Streetlight System for Sustainable Energy Efficiency and Smart Urban Management*, which proposes adaptive lighting systems that adjust illumination based on traffic density, environmental conditions, and time-based patterns to reduce energy consumption while maintaining public safety. Aditya has conducted mathematical research on chaotic systems through his paper *Spreadsheet-Based Coupling of Henon and Logistic Maps*, where he developed a model coupling chaotic maps using variable coupling factors to study synchronization and complex system behavior. The research was published in the *International Journal of Mathematics Trends and Technology.* Aditya has contributed to mechanical engineering innovation. He designed an automatic thread-pulling machine to separate flat-knitted garment components, improving manufacturing efficiency and worker safety. A patent application for this system was filed in February 2025. Aditya has gained industry exposure through technical internships at TerraTech (Dubai), Prakriti Creations, and Vandana Solvex, where he worked on energy systems, machine automation, and industrial process optimization.