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A Survey on Real-Time Sensor-Based Systems for Energy Monitoring and Carbon Emission Estimation: Technologies, Architectures, and Research Gaps

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***Abstract* - Global energy demand has jumped and produced a rise in the emission of greenhouse gases (GHG), which has made it difficult for sustainable development and transport systems. Current monitoring practices are largely siloed; carbon accounting currently takes place only in an annual audit and energy metering is primarily about billing and load management.**

Focusing on recent development, the survey examines the advancements in energy monitoring, carbon emission estimation systems that are designed to involve sensors in real-time. Literature is categorized into pertinent areas including energy monitoring using the Internet of Things, smart grid, carbon emission estimation methods, data process, load balancing and network security. Hardware-based components, such as power meters, CO sensors, and environmental sensors, are typically added to existing systems.

Trends such as visualization middleware, AI/ML simulations and quick prototyping are also emerging. The review reveals that there is a significant need for a low-cost holistic embedded system that can simultaneously measure real-time energy consumption, estimate carbon emission at a specific time using dynamic emission factors and track the ambient CO concentration in a single architecture.

The use of a structured foundation to develop such integrated systems is provided by this survey, which identifies suitable hardware infrastructures, communication protocols and algorithmic frameworks.

***Index Terms*—carbon emission monitoring, CO_2 sensors, edge computing, embedded systems, energy monitoring, ESP32, Internet of Things, machine learning, MQTT, NDIR sensors, PZEM-004T, real-time systems, smart metering, sustainable development**

I. INTRODUCTION

The connection between energy consumption and the environment. Sustainability is one of the new frontier areas of research. Electrical and Computer Engineering (ECE). According to the Human-made, Man-Made.Man-made, Anthropogenic. Climate change impacts on the environment are caused partly by increased electricity use. increase in atmospheric CO_2, contributing to global warming and sea and extreme climate change events. On top of that, in residential, commercial, Only at institutional facilities would the need to monitor at the same time arise. The measurement, description and quantification of electrical loads and their environmental effects has never been more critical. been more urgent.

In the past, monitoring energy and tracking carbon emissions had been done in these ways: Were used as separate units. Traditional Supervisory Control and Data Acquisition (SCADA) systems and utility-grade power meters are the main objects of focus. primarily focusing on billing accuracy as well as grid stability, without In-built facility to measure or calculate actual carbon in real-time footprints. Rather, infrastructures of environmental monitoring have developed. Difficult to measure parameters of the atmosphere like the CO_2 concentration: don't have the integration to correlate these readings with. The motives behind their electricity usage patterns. This bifurcated The significant latency of the approach to carbon accounting Edit The lack of a unified way to create workflows and access to automated tools makes it hard for facility managers to manage complex facilities and their operations. Using control systems to allow for data-driven control. [1], [2].

The coming of the Internet of Things (IoT), low-power Rising demand for microcontrollers, and near ubiquitous wireless connections has spurred a paradigm shift. Internet of Things and ESP8266.Today's Embedded systems using Espresso! The ESP32 System-on-Chip provide a dual core processing of 240 MHz. In conjunction with built-in Wi-fi and Bluetooth, with multiple sensors can be polled at the same time, Local computation, and cloud telemetry within a single compact, low-cost node. These features, and factory-calibrated, The PZEM-004T is ideally suited to operate with galvanically isolated power transducers like the PZEM-004T and other

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similar devices. A high precision Non Dispersive Infrared (NDIR) CO_2 sensor Make: Architecturally it is able to be built by integrating a unified monitoring system. that connects the two worlds that have been divided [3], [4].

This survey addresses the following research questions:

1) What IoT and embedded system architectures have been deployed for real-time electrical energy monitoring, and what are their key limitations?
2) Which power metering transducers are most suitable for accurate, safe, and low-cost energy measurement?
3) How have CO_2 and environmental sensors been integrated into IoT monitoring frameworks?
4) What communication protocols and cloud platforms best support unified energy-environment telemetry?
5) How is carbon emission estimated from electrical energy data in real-time systems?
6) What AI/ML techniques are most effective for forecasting energy consumption and carbon emissions?
7) What critical research gaps persist across these domains?

The remainder of this paper is organised as follows. Section II describes the review methodology. Sections III through IX analyse the surveyed literature across the seven thematic domains. Section X presents a comparative analysis and identifies research gaps. Section XI concludes the paper.

II. REVIEW METHODOLOGY

Our review focused on papers from 2020–2025 available on Elsevier Science Direct, IEEE Xplore, Springer Link, and MDPI. In total, we review 30 papers, classified across seven thematic categories, summarized in Table I. 2025. Search keywords included combinations of: IoT energy monitoring, real-time carbon emission estimation, embedded systems power metering, CO2 sensor IoT, MQTT energy dash-board , PZEM-004T, ESP32 energy monitoring, and machine learning carbon footprint. Papers were selected based on direct relevance to the core research problem: unified, real-time measurement of electrical energy consumption and carbon emission estimation using embedded sensor systems. A total of 30 papers are reviewed and classified across seven thematic categories, as summarised in TableI.

III. IOT-BASED EMBEDDED ENERGY MONITORING SYSTEMS

The first layer of any federated carbon-monitoring system is the deployment of internet-of-things (IoT)-based embedded nodes that can measure energy in real-time at the building, campus, and industrial levels.

Zhang et al. [1] proposed a city-scale smart carbon monitoring platform leveraging IoT cloud architecture for small cities. While the platform demonstrated effective real-time data aggregation, it required substantial infrastructure investment unsuitable for building-level deployment. Mirani et al. [2] developed an industrial IoT energy monitoring system incorporating edge data processing. By pre-processing electrical parameters at the node level, the system significantly reduced cloud bandwidth requirements, though CO_2 and environmental sensing were outside the system's scope.

Monton et al. [5] deployed an IoT-based energy monitoring system for university facilities using ACS712 current sensors and ESP8266 modules. The system provided granular per-appliance energy breakdowns but lacked environmental sensing. Amin et al. [6] implemented a real-time building energy monitoring system at Universiti Malaya using IoT infrastructure, correlating electricity usage with estimated carbon emissions, though without integrated environmental sensors.

Rhesri et al. [4] presented a low-cost IoT platform for three-phase energy monitoring in a university campus using Modbus RTU, InfluxDB, and Grafana, identifying severe transmission data loss risks when migrating from wired SCADA to wireless IoT. Paguay et al. [7] engineered an ESP32-based embedded platform integrating temperature, flow, and current sensors to automate real-time Coefficient of Performance (COP) diagnostics for heat pumps. Bonavolonta` et al. [8] proposed a LoRaWAN and MQTT-based monitoring framework for renewable energy communities operating under soft real-time constraints. Patnaik and Gupta [3] designed an IoT-based Smart Energy Monitoring System (SEMS) using Arduino Uno and Wi-Fi, monitoring real-time energy via a web interface with threshold-based notifications, without any CO_2 sensing capability.

IV. SMART POWER METERING HARDWARE AND SENSOR TECHNOLOGIES

The accuracy of any energy monitoring architecture is intrinsically determined by its transducers. Three primary current sensing technologies dominate the IoT landscape: the ACS712 Hall Effect sensor, the SCT-013 split-core current transformer, and the PZEM-004T dedicated energy metering module.

The **ACS712** operates on the Hall effect principle, converting the magnetic field generated by the live conductor into a proportional analogue voltage. While inexpensive and capable of measuring both AC and DC currents, it is an intrusive sensor requiring the live wire to be cut and routed through the IC, exposing the circuit board to mains voltage. It is also susceptible to electromagnetic interference (EMI) and thermal drift [5].

The **SCT-013** split-core current transformer clamps around the insulated live wire and induces a proportional secondary current via electromagnetic induction, providing galvanic isolation. However, integrating it requires custom signal conditioning circuits with burden resistors and DC bias networks, along with phase-angle correction algorithms for accurate active power calculation [9].

The **PZEM-004T** incorporates a dedicated Energy Metering System-on-Chip (SoC) that calculates RMS voltage, RMS current, active power, total energy (kWh), AC frequency, and power factor internally. It communicates the processed metrics to the microcontroller via a UART interface using the Modbus RTU protocol, completely offloading heavy digital signal processing and freeing computational resources for MQTT, display, and sensor tasks [10].

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Al-Sammak et al. [10] developed an adaptive algorithm using the PZEM-004T that dynamically modulates transmission frequencies based on load changes, achieving over 76% energy savings in IoT node power consumption. Garce´s et al. [9] engineered a smart meter using ZMPT101B voltage transformers and SCT-013 sensors capturing Total Harmonic Distortion (THD) and other advanced power quality metrics, though high-resolution processing introduced computational latency. Jadhav et al. [11] developed a mobile application for carbon footprint calculation using electricity consumption inputs, demonstrating the value of user-facing energy data visualisation.

V. CO_2 AND ENVIRONMENTAL SENSOR INTEGRATION

The measurement of ambient CO_2 concentration serves both as a direct environmental metric and as a proxy for occupancy density and ventilation effectiveness. Two principal transduction technologies are employed: Metal Oxide Semiconductor (MOx) sensors and Non-Dispersive Infrared (NDIR) spectroscopy.

MOx sensors (e.g., MQ-135) heat a tin dioxide (SnO_2) sensing layer to 200–400°C. Reducing gases react with adsorbed oxygen on the surface, causing a measurable drop in electrical resistance. While extremely inexpensive, MOx sensors are non-selective, exhibiting cross-sensitivity to a broad spectrum of Volatile Organic Compounds (VOCs), humidity variations, and temperature fluctuations, rendering them unsuitable for precise carbon accounting [12].

NDIR sensors leverage the Beer-Lambert law: CO_2 molecules absorb infrared radiation at a distinct 4.26 μm wavelength. An optical bandpass filter isolates this wavelength, making NDIR sensors highly immune to cross-sensitivity from VOCs or other atmospheric gases. Modern NDIR modules incorporate Automatic Baseline Calibration (ABC) algorithms to compensate for long-term optical drift, maintaining accuracy without manual recalibration [12], [13].

Sabando-Bravo et al. [12] assessed a LoRaWAN-based wireless sensor network for urban CO_2 telemetry using MQ-135 sensors, confirming their severe susceptibility to environmental variables and lack of manufacturer accuracy bounds. Afreen and Bajwa [13] architected an IoT platform for real-time tracking of temperature, humidity, and trace gas concentrations in cold storage, focused on alert generation without closed-loop actuation. Shinde et al. [14] deployed IoT sensors tracking electricity consumption, water usage, and mobility-related CO_2 emissions across a smart campus, though the system required extensive sensor deployment and complex infrastructure. The survey paper on IoT-driven carbon footprint reduction in higher educational institutions [15] further highlights the applicability of CO_2 sensing within campus environments.

VI. MICROCONTROLLER ARCHITECTURES AND EDGE-TO-CLOUD COMMUNICATION

The selection of edge processing hardware and the wireless communication middleware fundamentally determines the latency, reliability, and power efficiency of any IoT monitoring deployment.

A. Edge Hardware Comparison

The 8-bit ATmega328P microcontroller found in the Arduino Uno operates at 16 MHz with only 2 KB of SRAM and no native networking hardware, rendering it unsuitable for modern secure IoT telemetry [3]. The **ESP32** SoC features a dual-core Tensilica Xtensa LX6 processor at 240 MHz, 520 KB of SRAM, and integrated Wi-Fi and Bluetooth. Its dual-core architecture supports FreeRTOS task pinning: Core 0 handles the TCP/IP stack and cryptographic TLS/SSL handshakes, while Core 1 is dedicated to UART-based PZEM-004T polling and I^2C-based sensor reads. This guarantees that network latency does not disrupt strict sensor timing [16]. The **Raspberry Pi 4** employs an ARM Cortex-A72 processor running a full Linux OS, enabling local MQTT broker hosting and complex Python analytics at the cost of 3–5 W continuous power consumption vs. ∼100 mW for the ESP32 [17].

B. MQTT Telemetry Protocol

The Message Queuing Telemetry Transport (MQTT) protocol operates on a publish/subscribe architecture explicitly designed for constrained IoT devices. The ESP32 publishes JSON payloads (voltage, current, power, energy, CO_2 ppm) to hierarchical topics; cloud subscribers receive data with configurable Quality of Service (QoS) levels. QoS 1 guarantees at-least-once delivery via broker acknowledgment (PUBACK), essential for accurate cumulative kWh and carbon accounting. MQTT's Last Will and Testament (LWT) feature enables automatic offline-status alerts when a node disconnects unexpectedly [16], [17].

Spaˇner et al. [16] developed an autonomous ESP32-driven off-grid prototype modulating power consumption using environmental forecasts and MQTT pipelines, though the ThingSpeak visualisation tier produced static dashboards. Dinmohammadi et al. [17] proposed a Raspberry Pi architecture for automated cloud-connected residential energy auditing but did not assess the energy footprint of the IoT hardware infrastructure itself.

VII. CARBON EMISSION ESTIMATION FROM ENERGY DATA

The core innovation of unified monitoring architectures is the real-time translation of electrical energy consumption (kWh) into equivalent carbon dioxide emissions ($kgCO_2e$) using:

$$E_{CO_2} = E_{kWh} \times GEF \tag{1}$$

where E_{CO_2} is the carbon emission in $kgCO_2e$, E_{kWh} is the energy consumed in kilowatt-hours, and GEF is the Grid Emission Factor in $kgCO_2e/kWh$.

Static emission factors are annualised scalar values published by regulatory bodies (e.g., the EPA or the BEE in India). While computationally trivial to embed, they systematically

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misrepresent real-time environmental impact because the proportional mix of energy generation—baseload coal, natural gas peaker plants, and intermittent solar and wind—fluctuates continuously [18], [19].

Dynamic marginal emission factors, obtained via real-time REST API calls to grid operators (e.g., Electricity Maps or WattTime), provide the instantaneous carbon intensity of the local grid at 5–15 minute resolution. When synchronised with hardware-level energy measurements, they yield a microscopically accurate profile of the facility's true carbon footprint [18].

The study on carbon emission estimation via the electricity-carbon nexus [18] articulated an advanced methodology coupling non-intrusive electrical load monitoring with dynamic grid carbon intensity, demonstrating high estimation fidelity but requiring extensive smart-meter datasets. Green IoT event detection [19] developed a microcontroller-based binary event classification framework for carbon monitoring in sensor networks, suppressing node-level power draw by up to 99.8%. Rani et al. [20] provided scope-wise campus carbon benchmarking (transport, electricity, LPG, printing) yielding a per-capita footprint of 8.66 tonnes CO_2 per person, though without real-time embedded sensor integration. Zhang et al. [21] designed a blockchain-based carbon footprint and energy auditing system using IoT meters, though blockchain overhead introduced high computational complexity and cost. Jiang et al. [22] proposed a campus carbon emission evaluation framework based on energy consumption data, focusing on evaluation methodology rather than embedded real-time sensing. The carbon footprint tracker using IoT and AI [23] demonstrated the potential of integrating AI models with sensor data for personalised emission tracking.

VIII. DATA VISUALISATION MIDDLEWARE AND DASHBOARD PLATFORMS

Translating continuous sensor telemetry into actionable operational intelligence requires a coherent middleware and visualisation stack.

The Node-RED software functions within a Node.js runtime environment because Node-RED provides a browser-based visual programming tool that utilizes flows. Experts claim that Node-RED allows for simple management of data. MQTT topics are subscribed to by a Node-RED instance so that JSON payloads are parsed while external grid APIs are queried for carbon footprint calculations. Because organized data is required, clean timestamped information is injected into a time-series database by Node-RED.

Engineers created InfluxDB as a specialized storage system for the reason that rapid-velocity IoT data with many timestamps needs careful handling. Intricate temporal queries, such as a rolling 4-hour moving average of carbon emissions, are supported by InfluxDB with great speed. It has been observed that InfluxDB manages large amounts of information with remarkable effectiveness. Because InfluxDB stores these records, the data remains available for analysis.

A direct link to InfluxDB is established by Grafana because this connection allows for dynamic multi-axis dashboards. These displays show immediate active power (kW), surrounding CO2 (ppm), and accumulated carbon emissions (kgCO2e) at the same time. Many people believe that Grafana helps with the visualization of intricate statistics. When footprint thresholds are exceeded, algorithmic alerting is supported by Grafana through Webhooks, Slack, or email. [4], [24].

Mofidul et al. [24] architected an end-to-end IIoT framework unifying edge-based AI with Isolation Forests for real-time electrical anomaly detection over encrypted MQTT, though model efficacy was constrained by the quality of historical training datasets. Rajule et al. [25] proposed a Green IoT smart campus framework with sensor-driven monitoring and dashboards, focusing primarily on energy optimisation rather than CO_2 sensing. Jadhav et al. [11] demonstrated that intuitive mobile visualisation of carbon footprint data significantly increases user engagement with sustainability metrics.

IX. AI AND MACHINE LEARNING FOR CARBON FOOTPRINT PREDICTION

The integration of AI/ML pipelines transforms descriptive energy monitoring into predictive carbon management, enabling proactive demand-side management strategies.

Long Short-Term Memory (LSTM) networks are a specialised derivative of Recurrent Neural Networks (RNNs) engineered to model temporal sequences. Their internal cell states—regulated by input, output, and forget gates—allow them to retain operational memory over extended periods, making them well-suited for forecasting energy load profiles from historical occupancy and environmental data. **Extreme Gradient Boosting (XGBoost)** iteratively builds decision trees and is extraordinarily resilient to overfitting, handles missing data elegantly, and requires significantly less computational power than LSTM. Frameworks like SHAP (SHapley Additive exPlanations) provide feature importance transparency, critical for validating AI logic before deploying automated load modifications [26], [27].

Meng and Noman [28] formulated SARIMAX architectures to forecast global CO_2 trajectories, modelling pandemic-induced emission anomalies, though the research lacked operational hardware integration. Hauck et al. [26] demonstrated that XGBoost achieves $R^2 = 0.9922$ for CO_2 emissions in manufacturing scenarios, substantially outperforming back-propagation networks which suffered overfitting rates of 10–16%. Nassef et al. [27] comprehensively evaluated FFNN, ANFIS, and LSTM for national carbon footprint modelling, achieving $R^2 > 0.98$ with a 70/30 train-test split. Recurrent ar-chitectures faced destabilisation due to the vanishing gradient problem. The performance comparison of deep learning mod-els [29] benchmarked LSTM, CNN-LSTM, and GRU models for CO_2 prediction, demonstrating the superiority of hybrid architectures. Dash and Mathur [30] integrated Gemini 2.0 AI into the EcoTrack application, achieving 96.4% accuracy in personalising sustainability recommendations, though the

TABLE I
COMPARATIVE SUMMARY OF THE 30 SURVEYED WORKS

Reference	Energy Monitor	CO_2 Sensor	Carbon Estimate	RT Dashboard
Zhang et al. [1]	✓	×	✓	✓
Mirani et al. [2]	✓	×	×	✓
Monton et al. [5]	✓	×	×	✓
Amin et al. [6]	✓	×	✓	✓
Rajule et al. [25]	✓	×	×	✓
Shinde et al. [14]	✓	✓	✓	✓
Jiang et al. [22]	✓	×	✓	×
Zhang et al. [21]	✓	×	✓	✓
Dash & Mathur [30]	×	×	✓	✓
Rani et al. [20]	✓	×	✓	×
[15]	✓	×	✓	×
[29]	×	×	✓	×
[23]	✓	×	✓	✓
Patnaik & Gupta [3]	✓	×	×	✓
Jadhav et al. [11]	×	×	✓	✓
Rhesri et al. [4]	✓	×	×	✓
Paguay et al. [7]	✓	×	×	✓
Bonavolonta` et al. [8]	✓	×	×	✓
Al-Sammak et al. [10]	✓	×	×	✓
Garce´s et al. [9]	✓	×	×	✓
Sabando-Bravo et al. [12]	×	✓	×	✓
Afreen & Bajwa [13]	×	✓	×	✓
Spaˇner et al. [16]	✓	×	×	✓
Dinmohammadi et al. [17]	✓	✓	×	✓
[18]	✓	×	✓	×
[19]	✓	×	✓	×
Mofidul et al. [24]	✓	×	×	✓
Meng & Noman [28]	×	×	✓	×
Hauck et al. [26]	×	×	✓	×
Nassef et al. [27]	×	×	✓	×

system relied on user-reported data rather than hardware sensor inputs.

X. COMPARATIVE ANALYSIS AND RESEARCH GAPS

A. Comparative Summary

Table I presents a consolidated comparison of the 30 surveyed papers across four key dimensions: energy monitoring, CO_2 sensing, carbon emission estimation, and real-time dashboard visualisation. A checkmark (✓) indicates the feature is present; a cross (×) indicates it is absent.

B. Identified Research Gaps

A systematic analysis of Table I reveals five critical research gaps:

Gap 1 — Lack of Unified Integration: Of the 30 surveyed works, none simultaneously combines real-time electrical energy measurement using a calibrated embedded transducer, ambient CO_2 monitoring via a high-precision NDIR sensor, and real-time dynamic carbon emission estimation from the measured energy data within a single, low-cost embedded node. Only one study [14] includes both energy monitoring and CO_2 sensing, but does not perform embedded carbon estimation.

Gap 2 — Static Emission Factors: Papers that perform carbon estimation predominantly employ static, annualised Grid Emission Factors. These fail to capture the minute-to-minute variability in grid carbon intensity caused by fluctuating renewable energy penetration, peak demand events, and fuel dispatch dynamics [18], [19].

Gap 3 — Absence of Edge-Level Carbon Computation: Most carbon estimation methodologies are performed retrospectively in cloud backends or desktop software. Very few studies demonstrate real-time, on-device carbon computation at the embedded system level [19].

Gap 4 — Limited Environmental Contextualisation: The vast majority of energy monitoring systems measure only electrical parameters (voltage, current, power, energy). Correlation of energy consumption with simultaneous, localised environmental metrics (CO_2 concentration, temperature, humidity) within a unified embedded node remains largely unexplored.

Gap 5 — Scalability of Low-Cost Solutions: Existing high-accuracy systems rely on expensive, infrastructure-heavy deployments (SCADA, enterprise-grade sensors), while low-cost systems sacrifice precision or scope. A unified, low-cost platform maintaining both energy accuracy and environmental sensing remains an open problem [3], [4].

XI. CONCLUSION

This survey systematically examined 30 peer-reviewed studies published between 2020 and 2025, covering the design, implementation, and evaluation of IoT-based systems for real-time energy monitoring and carbon emission estimation. The reviewed literature confirms a maturing ecosystem of embedded energy monitoring hardware, cloud communication protocols, and AI-driven predictive models. However, five critical research gaps persist.

No existing low-cost embedded system integrates real-time electrical energy measurement, ambient CO_2 sensing, and instantaneous carbon emission estimation within a single unified architecture. The proposed project—*Design of a Real-Time Sensor-Based System for Energy and Carbon Emission Monitoring*—directly addresses these gaps. By leveraging the PZEM-004T for calibrated electrical measurement, an NDIR CO_2 sensor for environmental monitoring, an ESP32 microcontroller for edge processing, and MQTT with a Grafana dashboard for real-time visualisation, the proposed system aims to deliver the first unified, low-cost, real-time energy and carbon emission monitoring platform validated for residential and institutional deployment.

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Future work will focus on hardware implementation, field-scale validation of emission estimation accuracy against certified carbon audit methodologies, and integration of LSTM-based predictive models for proactive demand-side carbon management.

REFERENCES

[1] H. Zhang, J. Zhang, R. Wang, and Y. Li, "Smart carbon monitoring platform under IoT-cloud architecture for small cities," *Wireless Networks*, vol. 27, no. 8, pp. 5561–5575, 2021.

[2] A. A. Mirani, A. Awasthi, N. O'Mahony, and J. Walsh, "Industrial IoT-based energy monitoring system using edge data processing," *Internet of Things*, vol. 5, no. 4, pp. 289–301, 2024.

[3] R. Patnaik and A. K. Gupta, "IoT based smart energy monitoring sys-tem," *International Journal for Technological Research in Engineering (IJTRE)*, vol. 7, no. 10, pp. 6945–6947, 2020.

[4] A. Rhesri, F. Aabadi, R. Bennani, Y. Ben Maissa, A. Tamtaoui, and H. Dahmouni, "Development of a low-cost internet of things platform for three-phase energy monitoring in a university campus," *IoT*, 2025.

[5] J. E. B. Monton, M. T. Dela Cruz, and R. C. Reyes, "IoT-based energy monitoring system for optimizing power consumption in university facilities," in *Proc. IEEE Int. Conf. on Intelligent Data Acquisition and Advanced Computing Systems (IDAP)*, 2024.

[6] N. Amin, O. Erixno, and N. A. Rahim, "Internet of things solution in the execution of real-time building energy monitoring system at Universiti Malaya campus building," in *Proc. IEEE Int. Conf. on Smart Energy Systems*, 2023.

[7] J. Paguay, A. Cuenca-Sa´nchez, and P. Proan˜o, "Smart IoT-enabled embedded platform for real-time energy efficiency assessment in heat pumps," *Engineering Proceedings*, 2025.

[8] F. Bonavolonta`, A. Liccardo, F. Mottola, and D. Proto, "Real-time monitoring of energy contributions in renewable energy communities through an IoT measurement system," *Sensors*, 2025.

[9] H. O. Garce´s, J. Godoy, G. Riffo, N. F. Sepu´lveda, E. Espinosa, and M. A. Ahmed, "Development of an IoT-enabled smart electricity meter for real-time energy monitoring and efficiency," *Electronics*, 2025.

[10] K. A. Al-Sammak *et al.*, "Optimizing IoT energy efficiency: Real-time adaptive algorithms for smart meters with LoRaWAN and NB-IoT," *Energies*, 2025.

[11] B. Jadhav, O. Lolage, S. Lohote, S. Lohar, S. Lonare, A. Lokhande, and L. Chaudhari, "Mobile based carbon footprint calculator and analyzer," *International Journal for Research in Applied Science and Engineering Technology (IJRASET)*, vol. 11, no. VI, pp. 2211–2215, 2023.

[12] K. E. Sabando-Bravo, M. Navia, and J. L. Zambrano-Martinez, "Optimizing CO_2 monitoring: Evaluating a sensor network design," *Journal of Sensor and Actuator Networks*, 2025.

[13] H. Afreen and I. S. Bajwa, "An IoT-based real-time intelligent monitor-ing and notification system of cold storage," *IEEE Access*, 2021.

[14] S. Shinde, P. Kulkarni, and A. Deshmukh, "IoT-enabled smart campus sustainability: A KPI-based approach to monitoring water, electricity and mobility," in *Proc. IEEE Int. Conf. on Smart Infrastructure and Sustainable Systems*, 2024.

[15] "IoT-driven carbon footprint reduction in higher educational institu-tions," *IEEE*, 2023.

[16] M. Sˇpaner, M. Truntic ˇ, and D. Hercog, "IoT-based off-grid solar power supply: Design, implementation, and case study of energy consumption control using forecasted solar irradiation," *Applied Sciences*, 2025.

[17] F. Dinmohammadi, A. M. Farook, and M. Shafiee, "Improving energy efficiency in buildings with an IoT-based smart monitoring system," *Energies*, 2025.

[18] "A carbon emission estimation method based on electricity-carbon nexus and non-intrusive load monitoring," *Applied Energy*, 2024.

[19] "Green IoT event detection for carbon-emission monitoring in sensor networks," *Sensors*, 2023.

[20] M. Rani, B. Vyas, V. Dahiya, and P. Acharya, "Carbon emission bench-marking in university campus: Strategic development toward net zero transition," *SSRG International Journal of Civil Engineering*, vol. 12, no. 6, pp. 190–200, 2025.

[21] X. Zhang, Y. Li, and H. Zhao, "Design and implementation of energy efficiency audit: Carbon footprint tracking and sustainable development path planning system for green economy enterprises based on blockchain technology," in *Proc. IEEE Int. Conf. on Artificial Intelligence and Sustainable Systems*, 2025.

[22] L. Jiang, H. Chen, and Y. Wang, "Carbon emission evaluation method and software for green campus energy systems," in *Proc. IEEE Int. Conf. on Sustainable Energy Systems*, 2023.

[23] "Carbon footprint tracker using IoT and AI," *IEEE*, 2023.

[24] R. B. Mofidul *et al.*, "Real-time energy data acquisition, anomaly detection, and monitoring system: Implementation of a secured, robust, and integrated global IIoT infrastructure with edge and cloud AI," *Sensors*, 2022.

[25] N. Rajule, M. Venkatesan, and S. Pawar, "A green IoT framework for sustainable smart campus energy monitoring and management," in *Proc. IEEE Int. Conf. on Intelligent Monitoring and Applications (ICIMA)*, 2025.

[26] S. Hauck, L. Greif, N. Benner, and J. Ovtcharova, "Advancing sus-tainable additive manufacturing: Analyzing parameter influences and machine learning approaches for CO_2 prediction," *Sustainability*, 2025.

[27] A. M. Nassef, A. G. Olabi, H. Rezk, and M. A. Abdelkareem, "Application of artificial intelligence to predict CO_2 emissions: Critical step towards sustainable environment," *Sustainability*, 2023.

[28] Y. Meng and H. Noman, "Predicting CO_2 emission footprint using AI through machine learning," *Atmosphere*, 2022.

[29] "Performance comparison of deep learning models for CO_2 prediction analyzing carbon footprint with advanced trackers," *IEEE*, 2023.

[30] A. Dash and B. Mathur, "EcoTrack: A mobile application for real-time carbon footprint tracking and sustainable living," in *Proc. IEEE Int. Conf. on Smart Environment and Green Technologies*, 2024.