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Edge Computing–Enabled Real-Time CO_2 Emissions Monitoring: A Low-Latency and Bandwidth-Efficient Architecture for Oil and Gas Sector

Suka Handaja and Bambang Yudho Suranta

Politeknik Energi dan Mineral Akamigas
Gajah Mada Street No. 38 Cepu, Blora, Indonesia.

Corresponding author: Suka Handaja (suka.budi@esdm.go.id)

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ABSTRACT - The oil and gas industry is facing increasing pressure to reduce carbon dioxide (CO_2) emissions while maintaining operational efficiency and regulatory compliance. However, conventional cloud-based emissions monitoring systems often suffer from latency, bandwidth limitations, and reduced reliability in remote operational environments. This study aims to explore the role and implementation of edge computing as an enabling technology for real-time CO_2 emissions monitoring in oil and gas facilities. The architecture of the proposed system integrates the Internet of Things (IoT) gas sensors, local data processing units, and cloud platforms for long-term analytics and reporting. The system is designed to process the emissions data closer to the source with the aim of significantly reducing latency, improving measurement reliability, and enhancing responsiveness to abnormal emissions events. The performance was subsequently evaluated through a distributed monitoring test scenario that simulated multiple emissions monitoring points under intermittent network connectivity conditions often experienced in remote oil and gas operations. The focus was on key performance indicators including data latency, bandwidth utilization, and system availability. The results showed that the edge-enabled architecture reduced average data latency from approximately 3.8 s to 0.9 s and data transmission volume by an estimated 79% through local preprocessing while maintaining monitoring availability above 96% during network disruptions. The trend reflected the ability of edge computing to provide a scalable and robust solution for continuous CO_2 emissions monitoring, particularly in geographically distributed and harsh operational environments often associated with oil and gas operations.

Keywords: edge computing, CO_2 emissions monitoring, oil and gas industry, internet of things (IoT), Real-time monitoring, environmental sustainability, ESG compliance, digital transformation.

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INTRODUCTION

The oil and gas industry is currently a significant source of anthropogenic carbon dioxide (CO_2) emissions which contributes substantially to climate change. The phenomenon presents challenges for the commitments of the industry to sustainable development and environmental performance. Environmental monitoring of CO_2 emissions is very important in sustainability assessments and industry decarbonization strategies. The mitigation and monitoring of CO_2 in the oil and gas industry have also been considered in Carbon Capture, Utilization, and Storage (CCUS) strategies where emissions monitoring and storage are integrated into operational workflows (Sugihardjo 2022). Moreover, digitalization has been associated with improved environmental performance because it enables better measurement, transparency, and optimization of energy systems (Diófási-Kovács & Judit 2023). Digital integration in firms was also correlated with reductions in emissions and enhanced innovation (Quttainah & Ayadi 2024).

A key enabler of industry decarbonization is advanced emissions monitoring that can provide accurate real-time data for operational decision-making, regulatory reporting, as well as environmental, social, and governance (ESG) compliance. However, conventional monitoring systems that depend on centralized cloud processing face specific challenges such as high latency, bandwidth pressures, and vulnerability in remote or harsh industrial environments.

These challenges are capable of hindering consistent data collection and system reliability (Roostaei et al., 2023). The situation leads to the introduction of edge computing which processes data near the source rather than in a remote cloud to address the limitations by reducing latency, improving reliability, and enabling local analytics and anomaly detection (Roostaei et al., 2023). The applications of the system in environmental monitoring (Yadav et al., 2025) and industrial CO_2 tracking (Christensen 2024) show the potential to transform the management and utilization of data in real-world scenarios.

Figure 1 shows an integrated Edge–IoT–Cloud architecture for real-time CO_2 emissions monitoring in oil and gas operations. The distributed IoT sensors continuously capture and process high-resolution emissions data at critical sources such as the flaring systems, combustion units, and vent stacks.

Moreover, edge computing nodes introduce localized intelligence by performing real-time data preprocessing, anomaly detection, and preliminary emissions analytics to significantly reduce latency, bandwidth dependence, and vulnerability to network disruptions common in remote and offshore facilities. The aggregated and validated data at the cloud level also support long-term analytics, regulatory reporting, ESG disclosure, and strategic decision-making to enable a balance between operational emissions control, regulatory transparency, and broader energy transition objectives. The limitations of conventional cloud-centric emissions monitoring motivate this study to introduce a novel system that positions edge computing as a strategic enabler of sustainable energy governance rather than a purely technical optimization layer.

The conceptual presentation in Figure 2 shows that the proposed framework explicitly connects real-time edge-level CO_2 emissions intelligence with broader energy transition objectives and the United Nations sustainable

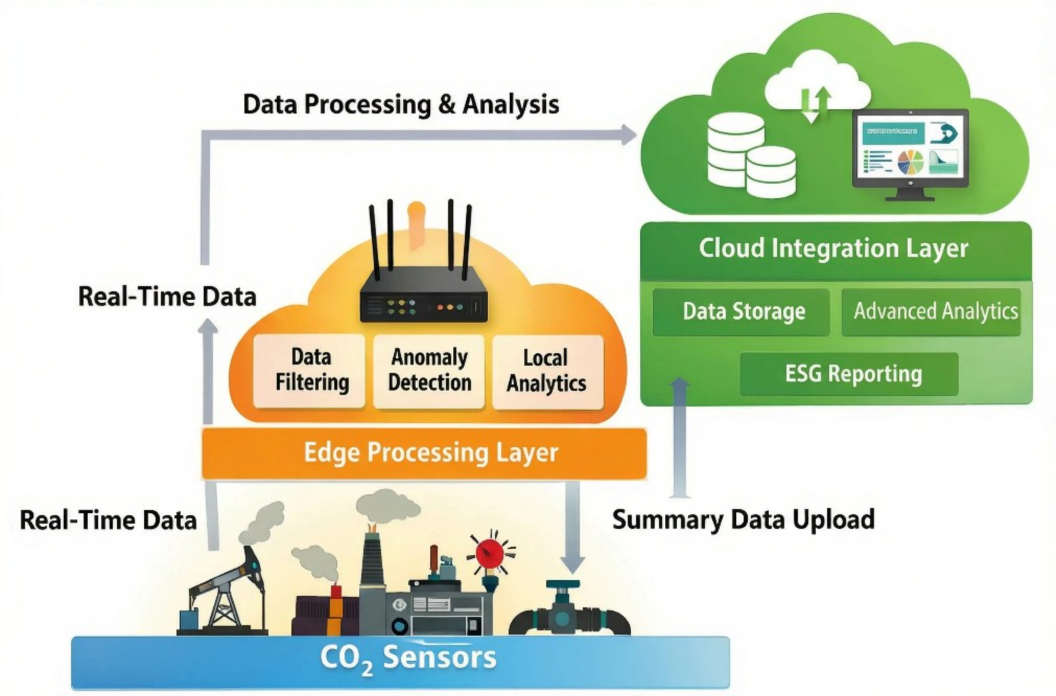

Figure 1. Edge-IoT-Cloud architecture for Co_2 emissions monitoring in the oil and gas industry.

development goals (SDGs) as a reflection of the relevance to global sustainability efforts. Figure 2 illustrates how an edge CO_2 monitoring system provides real-time emissions data to improve operational performance in the oil and gas industry. The collected data supports the development of sustainable energy systems, cleaner industrial processes, and enhanced climate resilience and adaptation. As a result, the proposed system contributes directly to the achievement of SDG 7 (Affordable and Clean Energy), SDG 9 (Industry, Innovation and Infrastructure), and SDG 13 (Climate Action).

The novelty of this study is in the development and evaluation of an integrated edge–IoT–cloud architecture specifically designed for real-time CO_2 emissions monitoring in oil and gas operations. Previous studies primarily emphasize either sensing technologies or cloud-based analytics but the current focus is on the system-level integration of distributed sensing, localized edge analytics, and cloud-based reporting infrastructures. The integration of real-time emissions data into digital analytics platforms was related to improved governance and sustainability outcomes (Samuel et al., 2025). The proposed system is also evaluated using quantitative performance metrics relevant to industrial monitoring systems such as data latency, bandwidth utilization, and monitoring reliability under simulated network disruption scenarios.

The trend shows that the objectives of this study are threefold including to (1) design a scalable Edge–IoT–Cloud architecture for real-time CO_2 emissions monitoring in oil and gas facilities, (2) evaluate the performance using key system performance indicators such as latency, bandwidth efficiency, and system availability, and (3) assess the operational benefits of localized edge analytics for improving the responsiveness and reliability of emissions monitoring systems in distributed industrial environments.

The objectives serve as the basis for the formulation of the study, which examines how an edge-enabled monitoring architecture improves the performance of real-time CO_2 emissions monitoring compared with conventional cloud-centric systems. The study further evaluates the extent to which edge computing reduces data latency and network bandwidth utilization in distributed emissions monitoring networks. Additionally, it analyzes how localized edge-level processing influences the reliability and responsiveness of emissions monitoring systems in remote oil and gas operational environments.

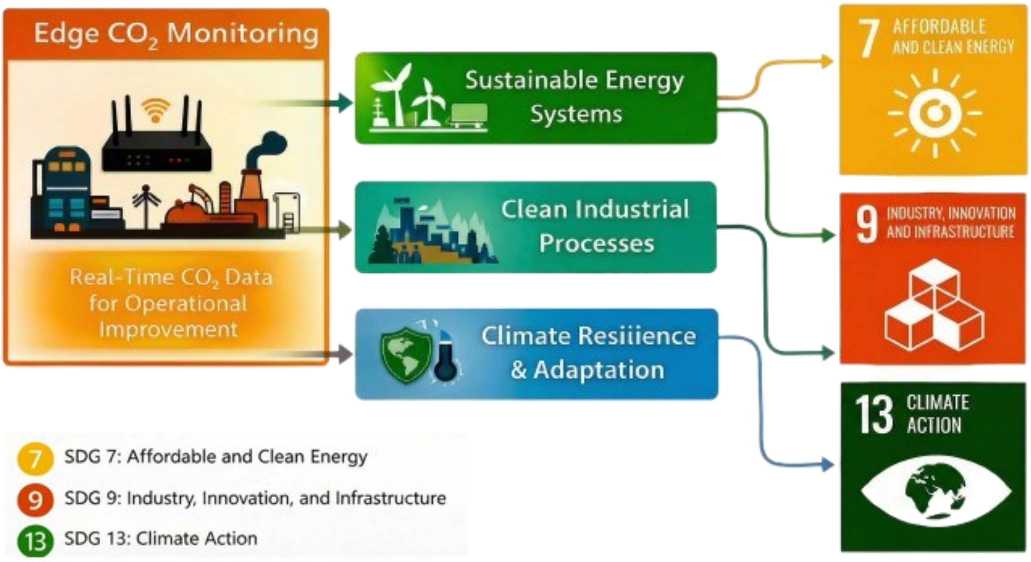

Figure 2. Edge computing-enabled CO_2 monitoring: advancing SDGs & energy.

Recent studies emphasized the role of digital innovation in bridging emissions monitoring with broader environmental performance and sustainability goals. The transition of industries toward more sustainable operations leads to the increasing recognition of real-time monitoring technologies as core components of environmental performance management systems. Therefore, the convergence of IoT, edge computing, and AI enhances emissions detection and reporting as well as facilitates the integration of performance data into sustainability metrics, environmental strategy formulation, and corporate ESG disclosure processes. The integration underscores the importance of digital-based emissions monitoring as an enabler of transparent performance evaluations and evidence-based environmental governance (Garcia et al., 2025).

Previous studies primarily emphasized technological performance improvements but the current focus was on the ability of edge computing to function as a translational layer between industrial operations and climate policy implementation particularly in hard-to-abate sectors such as oil and gas. This is due to the fact that greenhouse gas emissions particularly CO_2 are a principal concern in industry. Therefore, there is a need for mitigation strategies that include carbon capture and broader emissions reduction frameworks (Ismukurnianto 2008) and the mapping of CO_2 source–sink dynamics relevant to carbon storage planning (Al Hakim et al., 2025).

The efforts to mitigate CO_2 emissions in oil and gas operations extend beyond monitoring to include source-sink matching and sequestration strategies such as screening CO_2 EOR projects in depleted reservoirs to balance emissions abatement and enhanced oil recovery (Pasarai et al., 2010). The integrated method in the proposed system connects operational decarbonization efforts with SDG-oriented sustainability targets to reinforce the role of digital infrastructure as a cornerstone of the energy transition.

METHODOLOGY

System architecture

The proposed system architecture adopted a layered design comprising three interconnected levels including the sensing, edge processing, and cloud integration layers as presented in Figure 3. The sensing layer consisted of distributed CO_2 sensors strategically deployed across critical oil and gas process units including flaring systems, combustion equipment, compressors, and vent stacks. These sensors continuously measured CO_2 concentration along with supporting process variables such as flow rate, temperature, and pressure. Moreover, the high-frequency data acquisition at the emissions source ensured a granular and accurate representation of real operational conditions. This was necessary to enable reliable quantification of emissions across both steady-state and transient process scenarios.

The sensing layer consisted of four distributed CO_2 monitoring nodes deployed across representative emissions sources in oil and gas process units including flare stacks, combustion heaters, compressor exhaust systems, and vent stacks. Each monitoring node was equipped with an industrial CO_2 sensor capable of measuring gas concentration in the range of 350 –10,000 ppm with a measurement accuracy of ±2%. The supporting process variables such as gas flow rate, temperature, and pressure were recorded in addition to CO_2 concentration to provide contextual information for emissions analysis. Sensor data were also sampled at a frequency of 1 Hz to enable high-resolution monitoring of both steady-state and transient emissions conditions.

The edge processing layer served as the primary computational component of the system. Each sensor was connected to an edge device equipped with a 1.0 GHz quad-core processor, 512 MB RAM, and local storage capacity of 64 GB. These edge devices were installed in proximity to the sensing infrastructure to enable low-latency data processing. The incoming sensor data streams at the layer experienced preprocessing operations such as noise filtering, data validation, and sensor drift compensation. Moreover, lightweight anomaly detection algorithms developed in line with rule-based thresholds and simplified statistical models were implemented to identify abnormal emissions patterns or equipment malfunctions.

The cloud integration layer provided the centralized services for long-term data storage, advanced analytics, and policy-oriented reporting. The edge nodes transferred concise data summaries, event flags, and validated datasets to cloud servers to be aggregated and integrated into

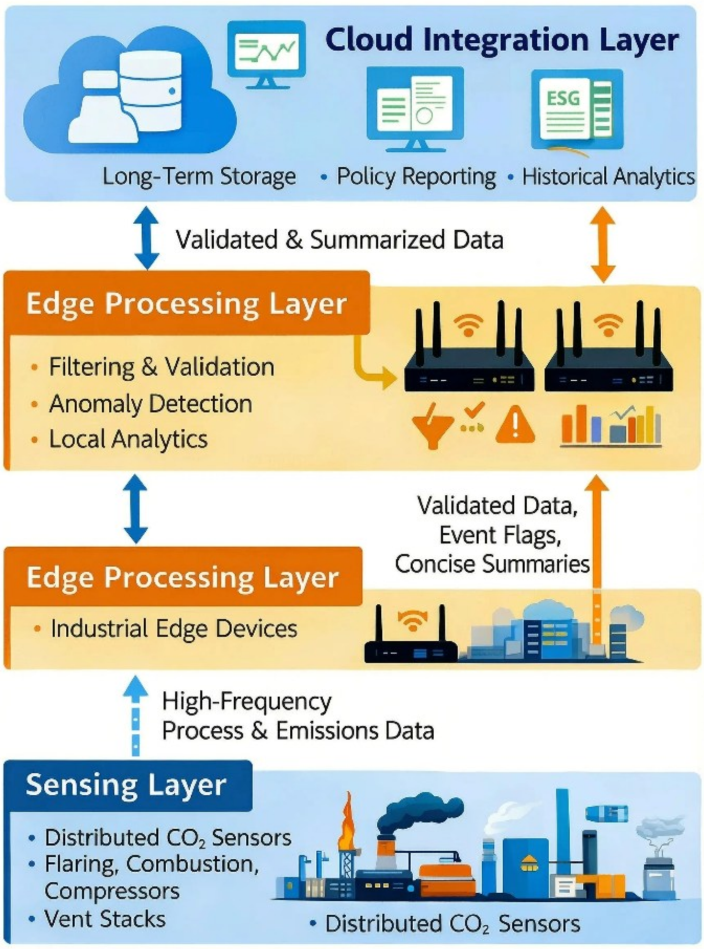

Figure 3. Proposed system architecture.

enterprise-level systems rather than transmitting raw sensor data. This cloud-based layer supported emissions inventory management, ESG and regulatory reporting, as well as historical trend analysis in line with environmental policy frameworks. Furthermore, the separation of real-time operational intelligence at the edge and strategic analytics in the cloud established a scalable, resilient, and energy-efficient monitoring architecture which enabled continuous emissions oversight while supporting sustainability governance and long-term decarbonization strategies in the oil and gas industry. The effectiveness of the proposed architecture was evaluated through an experimental monitoring system deployed in a simulated oil and gas operational environment to represent distributed emissions sources. The test configuration consisted of four CO_2 sensor nodes, four corresponding edge computing devices, and one centralized cloud server.

The monitoring system operated continuously over a seven-day observation period during which both normal operational and simulated abnormal emissions events were generated. The network conditions were varied to replicate realistic industrial scenarios. These included stable connectivity conditions for onshore facilities with reliable network access and intermittent connectivity for remote or offshore installations with periodic network disruptions. Sensor data were sampled at 1-second intervals to produce high -resolution time-series data for analysis. The monitoring system generated both routine and controlled anomaly events such as temporary CO_2 concentration spikes exceeding predefined thresholds during the test.

Data processing and analysis

Edge computing was observed to have substantial potential for enhancing environmental monitoring systems by enabling localized data processing and real-time analytics. However, existing literature has only focused on the limitations of current edge analytics architectures in addressing efficient resource allocation under constrained and heterogeneous environments (Nayak et al., 2022). The need for deeper investigation into trade-offs between quality attributes such as latency, resource utilization, and data veracity was also reported (Ashouri et al., 2021). Furthermore, the complexity of resource allocation strategies across the edge-cloud continuum continues to pose challenges in terms of balancing latency, cost, and throughput in IoT deployments (Dankolo et al., 2025).

The benefits of edge computing integration were quantified through a comparative performance analysis conducted between two monitoring architectures, as illustrated in figure 4. First, Cloud-Centric Architecture was used as the baseline system with raw sensor data streams transmitted directly from the sensing layer to the cloud server for processing. All preprocessing, anomaly detection, and analytics tasks were performed centrally in the cloud. Second, Edge-Enabled Architecture was the proposed system

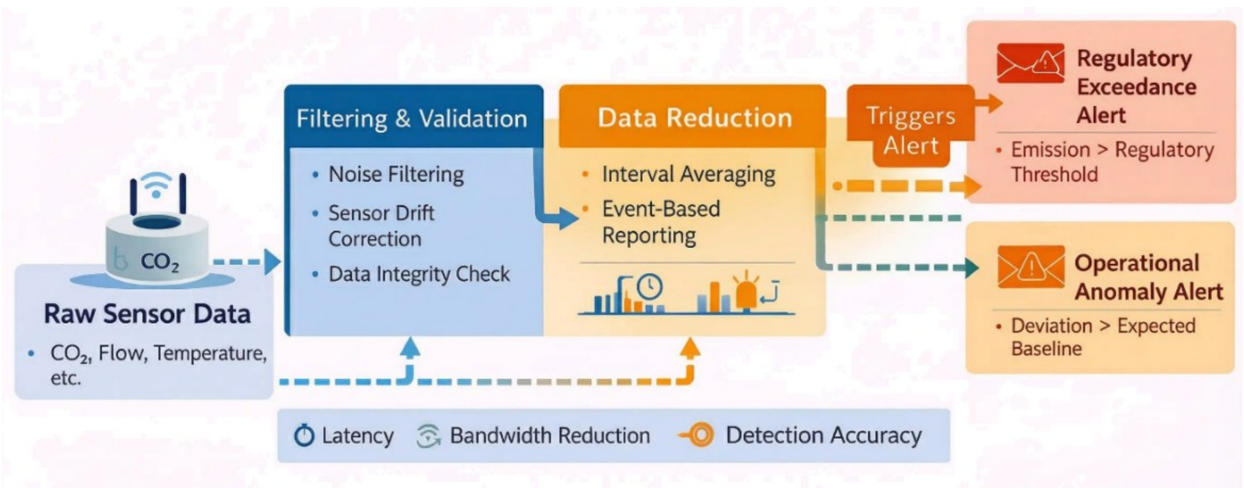

Figure 4. Policy-oriented data processing.

Table 1. Key performance indicators (KPIs) and evaluation metrics for edge-enabled CO_2 emissions monitoring system.

KPI	Definition	Evaluation Metric	Measurement Method	Policy/Operational Relevance
Data Latency	Time delay between emissions occurrence and data availability for alerting or reporting	Latency (seconds)	Timestamp comparison between sensor data acquisition and alert generation/cloud receipt	Enables timely mitigation actions and rapid response to regulatory exceedances
System Reliability	Ability of the monitoring system to operate continuously under varying network conditions	System uptime (%)	Ratio of successful monitoring duration to total observation period	Ensures continuous MRV compliance and data availability for audits
Bandwidth Utilization	Volume of data transmitted from field devices to cloud infrastructure	Data transmission volume (MB/day)	Comparison of transmitted data size with and without edge preprocessing	Reduces communication costs and supports scalable deployment in remote facilities

where the preprocessing, data reduction, and anomaly detection were performed locally at the edge nodes. Only validated data summaries and event notifications were transmitted to the cloud platform. Both architectures were evaluated using the same sensor data streams, network conditions, and operational scenarios to ensure fair comparison. The performance differences were measured using several key performance indicators (KPIs) including data latency, bandwidth utilization, system reliability, and event detection responsiveness.

Latency was calculated by comparing timestamps between sensor data acquisition and alert generation. Bandwidth utilization was evaluated by measuring the total volume of transmitted data between field devices and the cloud platform. System reliability was also assessed based on monitoring uptime during simulated network disruptions while event detection responsiveness was evaluated by measuring the time required to identify emissions threshold exceedances.

The evaluation framework enabled quantitative assessment of how edge-enabled processing improved monitoring performance compared with conventional cloud-based architectures. The results provided empirical evidence of the operational advantages of edge computing in supporting real-time emissions monitoring, improving system resilience, and enabling scalable deployment of monitoring infrastructures in geographically distributed oil and gas facilities.

Performance evaluation

The performance of the proposed edge-enabled CO_2 emissions monitoring system was evaluated using a set of KPIs that reflected both technical efficiency and regulatory relevance. The KPIs included data latency, system reliability, bandwidth utilization, and responsiveness to emissions events. Data latency was defined as the elapsed time between emissions occurrence at the sensing point and alert generation or data availability for reporting and was considered a critical factor for timely mitigation and regulatory compliance. Moreover, system reliability was assessed through the continuity of monitoring functions under varying network conditions including intermittent connectivity scenarios common in remote and offshore oil and gas operations.

Bandwidth utilization was evaluated by quantifying the reduction in transmitted data volume achieved through edge-level preprocessing and aggregation. Meanwhile, responsiveness to emissions events was measured through the ability of the system to promptly detect and flag regulatory exceedances and operational anomalies in line with MRV requirements. The benefits of edge computing integration were quantified through a comparative performance analysis with a conventional cloud-only monitoring architecture where raw sensor data were continuously transmitted to centralized servers for processing. Both architectures were evaluated under identical operational and network conditions to ensure a fair comparison. The performance improvements were expressed in terms of percentage reductions in data latency and bandwidth consumption as well as enhanced event detection responsiveness. This comparative evaluation framework provided empirical evidence of the advantages of edge-enabled monitoring in supporting real-time emissions oversight, strengthening compliance with environmental regulations, and enhancing the operational feasibility of large-scale emissions monitoring systems in the oil and gas industry.

RESULT AND DISCUSSION

Performance evaluation

- Latency Performance Comparison

Latency is a critical metric for real-time emissions monitoring because delayed data processing can prevent timely detection of abnormal events. Figure 5(a) presents the comparison between the conventional cloud-centric monitoring architecture and the proposed edge-enabled system.

The results showed that the average end-to-end latency in the cloud-only architecture reached approximately 3.8 seconds primarily due to continuous transmission of raw sensor data to the cloud server and centralized processing delays. Meanwhile, the edge-enabled architecture achieved an average of 0.9 seconds which represented a reduction of approximately 76%.

The improvement was primarily attributed to local preprocessing and anomaly detection performed directly at the edge nodes. The processing of the data near the sensing point allowed the system to eliminate the need to transmit large volumes of raw data before analysis. Subsequently, the reduced latency significantly enhanced the ability of the system to detect abnormal emissions events in near real-time which was particularly important for operational safety and emissions control in oil and gas facilities.

- Bandwidth Utilization and Data Reduction

Bandwidth consumption is another major challenge in large-scale emissions monitoring systems particularly in geographically distributed facilities where network capacity is probably limited. Figure 5(b) shows the total daily data transmission volume for both monitoring architectures.

The experimental results reflected that the cloud -centric system transmitted approximately 520 MB/ day of raw sensor data. Meanwhile, the edge-enabled architecture reduced data transmission to approximately 110 MB/day which represented a 79% reduction. This was achieved through several edge-level data processing mechanisms including temporal aggregation, noise filtering, and event-based reporting. The edge nodes transmitted only validated summaries and anomaly alerts to the cloud rather than continuously transferring raw time-series data. Therefore, the network load was significantly reduced without compromising the availability of critical emissions information. The reduced bandwidth requirement enabled more scalable deployment of emissions monitoring systems across multiple facilities particularly in offshore installations or remote production sites where communication infrastructure could be constrained.

- System Reliability Under Network Disruptions

Monitoring system reliability is particularly important in oil and gas operations where network connectivity can be unstable due to environmental conditions or infrastructure limitations. The system robustness was evaluated by conducting experiments under both stable network conditions and intermittent connectivity scenarios.

Figure 5(c) compares system uptime between the cloud-centric and edge-enabled architectures. Both systems achieved similar performance levels under stable network conditions with uptime exceeding 99%. However, pronounced differences were observed under intermittent network conditions. The cloud-centric system experienced a significant reliability drop to approximately 82% uptime due to the disruption of the monitoring functionality whenever network connectivity to the

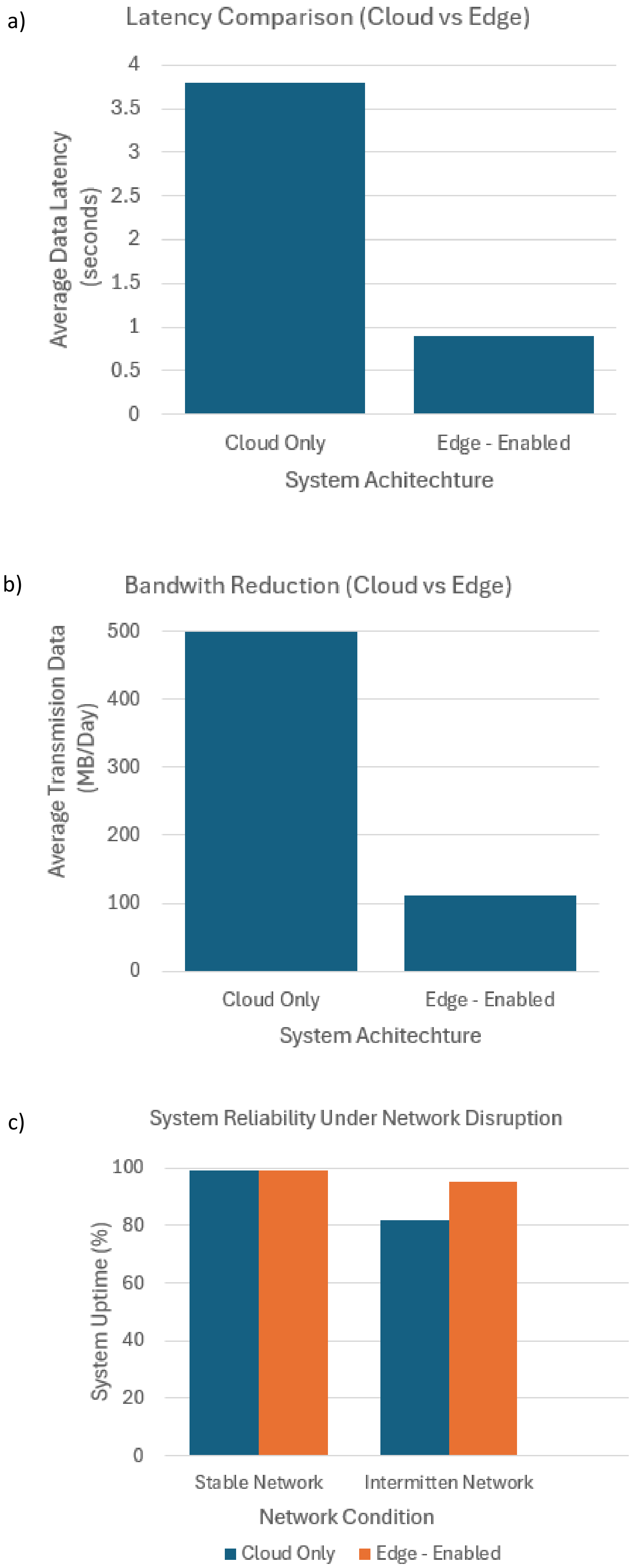

Figure 5. (a). Average data latency comparison for edge vs Cloud; (b). Average data reduction comparison for edge vs cloud; (c). average system reliability under network disruption comparison for edge vs cloud.

Table 2. KPIs for edge-enabled CO_2 emissions monitoring systems.

KPI Category	Metric Definition	Edge-Enabled System (Reported Range)	Cloud-Only Baseline	Evidence from Literature
Data Latency	End-to-end delay from sensor acquisition to actionable output	~490 μs – 2.6 s	~560 μs – 14.8 s	Edge computing reduced latency by ~13% in laboratory pilots and by up to ~80% in real urban field deployments (Malhotra, 2025)
Latency Reduction	Relative improvement compared to cloud-centric architecture	~13% (lab) to >80% (field)	Reference	Showed consistently across IoTEC pilots and multi-node air quality monitoring systems (Roostaei, et al., 2023)
Bandwidth Utilization	Reduction in uplink data transmission volume	~50–62% reduction	100% raw data transmission	Local preprocessing and aggregation at the edge significantly reduced network load (Roostaei, et al., 2023)
Data Accuracy	Agreement with reference measurements	≈95% accuracy	Comparable but with higher noise	Field deployments confirmed high data fidelity when edge-based validation and filtering were applied (Siddiqui, Rabbani, Akhtar, Suneel, & Naik, 2025)
Detection Performance	Error reduction in pollutant/emissions estimation	MAE reduced by ~63% ($PM_{2.5}$ proxy)	Higher estimation error	Edge analytics improved detection accuracy and reduced estimation error in real-time monitoring scenarios (Malhotra, 2025)
System Responsiveness	Time to trigger alerts relative to regulatory thresholds	<500 ms	Seconds to minutes	Edge–blockchain IoT systems achieved sub-second responsiveness, suitable for regulatory alarm thresholds (Alabdulkreem, et al., 2025)
Operational Resilience	Ability to operate during network disruption	Maintained local monitoring	Degraded or unavailable	Edge nodes ensured continued MRV functionality under intermittent connectivity conditions (Yadav, et al., 2025)

Table 3. Explicit mapping of edge-enabled CO_2 emissions monitoring to SDGs and energy transition objectives.

SDG	SDG Target	Relevant KPI/Technical Outcome	Contribution of Edge-Enabled Monitoring	Policy and Energy Transition Relevance
SDG 9 Industry, Innovation and Infrastructure	9.4: Upgrade infrastructure and retrofit industries for sustainability	Latency reduction (13–80%), bandwidth reduction (50–62%)	Enables digital upgrading of existing oil and gas infrastructure with minimal communication and energy overhead	Supports modernization of legacy energy assets during the transition period without requiring full asset replacement
SDG 12 Responsible Consumption and Production	12.4: Environmentally sound management of chemicals and emissions	Detection accuracy (~95%), improved anomaly detection	Provides continuous and accurate emissions monitoring, reducing unreported or delayed emissions events	Strengthens compliance mechanisms and supports responsible industrial operations
SDG 13 Climate Action	13.2: Integrate climate measures into policies and planning	Sub-second system responsiveness (<500 ms), real-time alerts	Enables rapid operational response when emissions exceed regulatory thresholds	Facilitates proactive climate mitigation actions rather than reactive reporting
SDG 7 Affordable and Clean Energy	7.3: Improve energy efficiency	Reduced data transmission and computational load	Lowers digital energy consumption associated with emissions monitoring systems	Balance digitalization with energy efficiency goals in the energy sector
SDG 16 Peace, Justice and Strong Institutions	16.6: Effective, accountable, and transparent institutions	High data integrity and validation at the edge	Improves credibility and transparency of emissions data for regulators and stakeholders	Enhance trust in MRV systems and emissions disclosure frameworks
SDG 17 Partnerships for the Goals	17.16: Multi-stakeholder partnerships	Cloud–edge integration for reporting and analytics	Facilitates data sharing between operators, regulators, and third-party auditors	Supports collaborative governance of emissions data across institutional boundaries

cloud server was lost. Meanwhile, the edge-enabled system maintained approximately 95–96% uptime because the local edge nodes continued performing data processing and anomaly detection even during temporary communication failures.

The capability shows the advantage of decentralized monitoring architectures in industrial environments where reliable network connectivity is not often guaranteed. Moreover, the performance evaluation reflects the ability of the proposed edge-enabled monitoring architecture to consistently outperform the conventional cloud-only method across all KPIs relevant to emissions MRV. The results were in line with the reports of the previous studies summarized in Table 2.

System responsiveness and operational resilience further reinforced the suitability of the proposed architecture for regulatory and policy-driven applications. This was because the edge-based systems consistently achieved sub-second alerting capabilities (<500 ms) which enabled rapid intervention when emissions exceeded the predefined regulatory limits.

The edge nodes maintained core monitoring and alerting functions even during intermittent cloud connectivity to ensure the continuity of MRV processes in harsh operational environments. The results collectively confirmed that edge computing provided a robust technological foundation for real-time CO_2 emissions monitoring, regulatory compliance, and operational decarbonization strategies in the oil and gas industry.

Implications for SDGs and energy transition

The performance results presented in Section 4. A showed that edge-enabled emissions monitoring architectures provided measurable and policy-relevant improvements in latency, data reliability, and operational resilience. These technical gains have direct implications for the achievement of multiple SDGs, particularly 9 on Industry, Innovation, and Infrastructure, 12 on Responsible Consumption and Production, and 13 on Climate Action. The near-real-time detection of CO_2 anomalies allowed the proposed architecture to strengthen the operational capacity of oil and gas facilities in managing emissions proactively rather than reactively. The significant reduction in data latency and bandwidth utilization supported the digitalization of legacy hydrocarbon assets from an energy transition perspective without imposing excessive communication or energy overheads. Edge computing enabled high-frequency emissions monitoring in geographically dispersed and infrastructure-constrained environments such as offshore platforms and remote gas processing plants.

This capability is critical during the transitional phase toward low-carbon energy systems where existing oil and gas infrastructure is required to operate with improved environmental performance while supporting the gradual integration of cleaner energy technologies. Moreover, the economic optimization of CCUS implementations including CO_2 injection strategies emphasizes the critical intersections between monitoring technologies and sustainability goals to reinforce the need for robust emissions monitoring systems (Iskandar & Musu 2025). Long-term emissions management strategies require understanding CO_2 storage potential and containment reliability in addition to real-time monitoring. These were assessed through criteria such as caprock quality indices for CO_2 sequestration sites (Destiana et al., 2025).

The observed improvements in data accuracy and detection performance further reinforced the role of edge computing in enhancing MRV systems. The accurate and timely measurement of emissions data reduced uncertainty in corporate greenhouse gas inventories and improved compliance with international reporting frameworks such as nationally determined contributions (NDCs) and voluntary ESG disclosure standards. In this context, edge-enabled monitoring served as a technical upgrade and also functioned as an enabling mechanism for transparent and credible climate governance within the energy sector.

Another important observation was that the resilience of edge-based architectures under intermittent connectivity conditions addressed a critical barrier to emissions monitoring in developing and resource-rich regions. The maintenance of local monitoring and alerting capabilities even during network disruptions allowed edge computing to ensure continuity of environmental oversight. This attribute supports equitable progress toward SDGs by enabling consistent emissions accountability across both advanced and remote industrial operations.

Policy implications

The results have several important implications for policymakers, regulators, and industry stakeholders associated with emissions governance and energy transition planning. First, the latency reduction and sub-second responsiveness of edge-enabled systems suggested that regulatory frameworks could increasingly recognize real-time or near-real-time emissions monitoring as a viable compliance mechanism.

This allows regulators to move beyond periodic reporting toward continuous compliance models particularly for high-risk emissions sources such as flaring systems and combustion units. Second, the substantial reduction in data transmission requirements achieved through edge preprocessing has implications for the design of MRV policies in remote and offshore environments. This shows the need for regulators and standard-setting bodies to consider incorporating edge computing architectures into technical guidance for emissions monitoring particularly where communication bandwidth and infrastructure limitations have historically constrained compliance. The recognition can lower implementation barriers and promote broader adoption of advanced monitoring technologies.

Third, the improved data accuracy and detection performance enabled by edge analytics strengthen the credibility of emissions data used for ESG reporting and carbon accounting. Policymakers can leverage the capability by promoting or mandating the use of edge-based validation and anomaly detection as part of certified emissions monitoring systems. This is capable of enhancing trust in reported emissions data and supporting more robust market-based mechanisms such as carbon pricing or emissions trading schemes.

Edge-enabled emissions monitoring is in line with policy objectives that emphasize digital innovation as a pathway to sustainable industrial transformation at a strategic level. The combination of engineering performance improvements with climate and energy policy goals allows edge computing to provide a pragmatic bridge between existing fossil-based operations and long-term decarbonization strategies. Therefore, the system represents a scalable and immediately deployable solution that can accelerate emissions transparency and accountability during the energy transition period.

CONCLUSION

In conclusion, this study confirmed that edge computing–based CO_2 emissions monitoring provided a technically robust and policy-relevant solution for enhancing environmental performance in the oil and gas industry. The results showed that the deployment of analytics and validation at the edge significantly improved data latency, transmission efficiency, and emissions detection accuracy compared to centralized cloud-only architectures. These performance gains directly strengthened the Measurement, Reporting, and Verification (MRV) processes which enabled more reliable compliance with emissions regulations while supporting operational decision-making in complex industrial environments. The results emphasized the strategic role of edge-enabled monitoring systems in accelerating energy transition and sustainable development objectives in addition to the technical contribution. This was because the proposed framework supported responsible production practices and proactive climate action without compromising system scalability or reliability by bridging digital infrastructure modernization with climate governance needs. Therefore, future studies should focus on large -scale multi-site deployments, integration of advanced machine learning models for predictive emissions forecasting, and compliance with changing international MRV standards to further enhance regulatory interoperability and long-term sustainability impact.

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DECLARATIONS

Author contribution

Suka Handaja, Bambang Yudho Suranta contributed equally as the main contributors of this paper. All authors read and approved the final paper.

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Competing interest

None

The use of AI or AI-assisted technologies

None

GLOSSARY OF TERMS AND SYMBOLS

Terms & Symbols	Definition	Unit
Anomaly Detection	The process of identifying abnormal patterns or deviations in emissions data that may show equipment malfunction, process upset, or regulatory exceedance	
Bandwidth Utilization	The volume of data transmitted from sensing and edge devices to cloud infrastructure, commonly measured to	

	evaluate network efficiency in monitoring systems
Carbon Capture, Utilization, and Storage (CCUS)	A set of technologies that capture CO_2 from industrial sources, use it in products or processes, or store it permanently to reduce greenhouse gas emissions
Carbon Dioxide (CO_2)	A primary greenhouse gas emitted from combustion, flaring, and venting activities in oil and gas operations, serving as a key indicator of environmental performance
Cloud Computing	A centralized computing paradigm that provides large-scale data storage, advanced analytics, and reporting services over the internet.
Cybersecurity Resilience	The ability of a monitoring system to maintain secure and reliable operation in the presence of cyber threats or network disruptions
Data Latency	The time delay between emissions occurrence at the source and data availability for alerting, analysis, or reporting
Data Reduction Ratio	A metric showing the proportion of raw sensor data volume reduced through edge-level preprocessing, filtering, and aggregation
Edge Computing	A distributed computing paradigm in which data processing and analytics are performed close to the data source, reducing dependence on centralized cloud servers
Edge Node	A localized computational device installed near sensors that performs real-time data preprocessing, validation, analytics, and anomaly detection
Environmental Performance	The measurable outcome of an organization’s activities related to emissions control, resource efficiency, and environmental impact mitigation.
Environmental, Social, and Governance (ESG)	A framework used to evaluate corporate sustainability performance, including emissions transparency, regulatory compliance, and ethical governance
Industrial Internet of Things (IIoT)	An extension of IoT applied in industrial environments, integrating sensors, communication networks, and analytics for operational monitoring and optimization
Internet of Things (IoT)	A network of interconnected physical devices embedded with sensors and communication technologies for data collection and exchange
Intermittent Connectivity	A condition in which network communication between field devices and cloud platforms is unstable or temporarily unavailable
Key Performance Indicators (KPIs)	Quantitative metrics used to evaluate the technical efficiency, reliability, and regulatory relevance of the emissions monitoring system
Measurement, Reporting, and Verification (MRV)	A systematic framework for quantifying emissions, documenting results, and verifying data accuracy to support regulatory compliance and climate policy.
Real-Time Monitoring	The capability to collect, process, and analyze emissions data with minimal delay, enabling immediate operational response.
Resource Allocation	The management of computational, storage, and communication resources across edge and cloud layers to optimize system performance.
Scalability	The ability of the monitoring architecture

	to maintain performance as the number of sensors, monitored locations, or data volume increases
Sensor Drift	Gradual deviation in sensor measurement accuracy over time due to aging, environmental exposure, or calibration loss
Sensing Layer	The system layer consisting of distributed CO_2 sensors and supporting instruments that acquire raw emissions data
Sustainable Development Goals (SDGs)	United Nations global goals addressing sustainability challenges, including climate action, responsible production, and industrial innovation
System Reliability	The ability of the monitoring system to operate continuously and correctly under varying environmental and network conditions
Temporal Granularity	The frequency at which emissions data are collected and processed, influencing the resolution of time-based analysis
Threshold-Based Detection	A rule-based analytics method that triggers alerts when emissions values exceed predefined limits
Wireless Sensor Network (WSN)	A network of spatially distributed sensors that communicate wirelessly to monitor environmental or process variables

REFERENCES

Al Hakim, M. F., Tony, B., Chandra, S., Nugraha, F. Y., & Nandiwardhana, D. (2025). Mapping The Potential CO_2 Source-Sinks for Carbon Capture Storage From Industry in Indonesia. *Scientific Contributions Oil and Gas*, 48(1), DOI: https://doi.org/10.29017/scog.v48i1.1626.

Alabdulkreem, E., Allafi, R., Arasi, M. A., Geetha, P., Nafie, F. M., Begum, A., . . . Vivek, S. (2025). Innovative IoT and blockchain integration for real-time urban air quality monitoring and an autonomous response system. Sustainable Computing: Informatics and Systems, 48, https://doi.org/10.1016/j.suscom.2025.101250.

Alkilany, A., & Dallaf, A. (2025). Edge Computing in IoT Networks: Enhancing Efficiency, Reducing Latency, and Improving Scalability. International Journal of Advanced Network, Monitoring and Controls.

Ashouri, M., Davidsson, P., & Spalazzese, R. (2021). Quality attributes in edge computing for the Internet of Things: A systematic mapping study. Internet of Things, 11(3), https://doi.org/10.1016/j.iot.2020.100346.

Bagkis, E., Hassani, A., Schneider, P., DeSouza, P., Shetty, S., Kassandros, T., . . . Khan, J. (2025). Evolving trends in application of low-cost air quality sensor networks: challenges and future directions. npj Climate and Atmospheric Science, 8, https://doi.org/10.1038/s41612-025-01216-4.

Christensen, M. S.-F. (2024). Leveraging the Industrial Internet of Things (IIoT) for Real-Time CO2 Monitoring, Measurement and Visualization: Technologies, Applications and Future Directions. Global Internet of Things and Edge Computing Summit (hal. 35 - 59, https://doi.org/10.1007/978-3-031-78572-6). Brussels, Belgium: Springer.

Dankolo, N. M., Radzi, N. H., Mustaffa, N. H., Arshad, N. I., Gabi, D., & Yusuf, M. N. (2025). Optimizing resource allocation for IoT applications in the edge cloud continuum using hybrid metaheuristic algorithms. Scientific Reports, 15, https://doi.org/10.1038/s41598-025-97648-2.

Destiana, S., Irawan, D., Aziz, P. A., & Merdekawati, I. (2025). CO_2 Storage Screening Criteria Based on Seal Capacity in Indonesia. Scientific Contributions Oil and Gas, 48(4), DOI: https://doi.org/10.29017/scog.v48i4.1829.

Diófási-Kovács, O., & Judit, N. (2023). Beyond CO2 emissions – The role of digitalization in multi-dimensional environmental performance measurement. Environmental and Sustainability Indicators, 18, https://doi.org/10.1016/

j.indic.2023.100252.

Fayos-Jordan, R., Segura-Garcia, J., Soriano-Asensi, A., Felici-Castell, S., Felisi, J. M., & Alcaraz-Calero, J. M. (2021). VentQsys: Low-cost open IoT system for CO2 monitoring in classrooms. Wireless Networks, 27, https://doi.org/10.1007/s11276-021-02799-5.

Ficili, I. G., Tricomi, G., & Puliafito, A. (2025). From Sensors to Data Intelligence: Leveraging IoT, Cloud, and Edge Computing with AI. Sensors, 25(6), https://doi.org/10.3390/s25061763.

Gamazo-Real, J.-C., Fernández, R. T., & Armas, A. M. (2025). Comparison of edge computing methods in Internet of Things architectures for efficient estimation of indoor environmental parameters with Machine Learning. Engineering Applications of Artificial Intelligence, 126, https://doi.org/10.1016/j.engappai.2023.107149.

Garcia, A., Saez, Y., Harris, I., Huang, X., & Collado, E. (2025). Advancements in air quality monitoring: a systematic review of IoT-based air quality monitoring and AI technologies. Artificial Intelligence Review, 58, https://doi.org/10.1007/s10462-025-11277-9.

Hasan, R., Khatoon, R., Akter, J., Mohammad, N., Kamruzzaman, M., Shahana, A., & Saha, S. (2025). AI-Driven greenhouse gas monitoring: enhancing accuracy, efficiency, and real-time emissions tracking. AIMS Environmental Science, 12(3), doi: 10.3934/environsci.2025023.

Iskandar, U. P., & Musu, J. T. (2025). Optimisasi Ekonomi Carbon Capture, Utilization, and Storage (CCUS): Pendekatan Iteratif Latin Hypercube Sampling dalam Menentukan Laju Injeksi CO_2. *Lembaga Publikasi Minyak dan Gas Bumi (*LPMGB), 59(1), DOI: https://doi.org/10.29017/LPMGB.59.1.1796.

Ismukurnianto, D. (2008). Mitigation of Carbon Dioxide and Green House Gas Emissions From Oil and Gas Industry in Indonesia. Scientific Contribution Oil and Gas, 31(1), 1 - 11. https://doi.org/10.29017/SCOG.31.1.856.

Malhotra, A. (2025). Real-Time Air Quality Monitoring Using Edge IoT Gateways. International Journal of Advanced Research in Computer Science and Engineering, 1(4), https://doi.org/10.63345/v1.i4.202.

Marquez-Zepeda, M. J., Santos-Ruiz, I., Pérez, E.-J., Navarro-Díaz, A., & Delgado-Aguiñaga, J.-A. (2025). Internet-of-Things-Based CO2 Monitoring and Forecasting System for Indoor Air Quality Management. Mathematical and Computational Applications, 30(2), https://doi.org/10.3390/mca30020036.

Metia, S., Nguyen, H. A., & Phuc Ha, Q. (2021). IoT-Enabled Wireless Sensor Networks for Air Pollution Monitoring with Extended Fractional-Order Kalman Filtering. Sensors, 21(16), https://doi.org/10.3390/s21165313.

Nayak, S., Patgiri, R., Waikhom, L., & Ahmed, A. (2022). A review on edge analytics: Issues, challenges, opportunities, promises, future directions, and applications. Digital Communications, 10(3), https://doi.org/10.1016/j.dcan.2022.10.016.

Pasarai, U., Iskandar, P. U., & Sismartono, D. (2010). Worksheet Screening Of Co2 Eor Sequestration Potential In Indonesia. *Scientific Contributions Oil and Gas*, 33(1), DOI: https://doi.org/10.29017/SCOG.33.1.806.

Quttainah, M. A., & Ayadi, I. (2024). The impact of digital integration on corporate sustainability: Emissions reduction, environmental innovation, and resource efficiency in the European. Journal of Innovation & Knowledge, 9(3), https://doi.org/10.1016/j.jik.2024.100525.

Rahmadani, A. A., Syaifudin, Y. W., Setiawan, B., Panduman, Y. Y., & Funabiki, N. (2024). Enhancing Campus Environment: Real-Time Air Quality Monitoring Through IoT and Web Technologies. Journal of Sensors And Actuator Networks, 14(1), https://doi.org/10.3390/jsan14010002.

Roostaei, J., Wager, Y. Z., Shi, W., Dittrich, T., Miller, C., & Gopalakrishnan, K. (2023). IoT-based edge computing (IoTEC) for improved environmental monitoring. Sustainable Computing: Informatics and Systems, 38, https://doi.org/10.1016/j.suscom.2023.100870.

Samuel, D.-K., Daniel, A.-M., & Jennifer, M.-F. (2025). Conducting a systematic literature review of environmental emissions performance and eco-innovation research. International Journal of Innovation Studies, https://doi.org/10.1016/j.ijis.2025.10.005.

Siddiqui, F., Rabbani, H., Akhtar, N., Suneel, S., & Naik, A. S. (2025). Scalable Environmental Monitoring System Using Iot And Edge Computing. International Journal of Environmental Science, 11(11s), DOI: https://doi.org/10.64252/ybsrxh42.

Sugihardjo. (2022). CCUS-Aksi Mitigasi Gas Rumah Kaca dan Peningkatan Pengurasan Minyak CO2. LPMGB, 56(1), DOI: 10.29017/LPMGB.44.3.709.

Yadav, L., Murugan, V., Vijayakanthan, A, K. B., Mathurkar, P., & Urkude, G. (2025). Integrating Edge Computing And Iot For Real-Time Air And Water Quality Monitoring Systems. International Journal of Environmental Sciences, 11(17), DOI:10.64252/z52kvj10.

Yavari, A., Mirza, I. B., Bagha, H., Korala, H., Dia, H., Scifleet, P., . . . Shafiei, M. (2023). ArtEMon: Artificial Intelligence and Internet of Things Powered Greenhouse Gas Sensing for Real-Time Emissions Monitoring. Sensors, 23 (18), https://doi.org/10.3390/s23187971.