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Artificial Intelligence for predictive analysis, efficiency improvement and reduction in carbon footprint during decommissioning and site remediation in oil and gas fields

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Abstract

This piece discusses how Artificial Intelligence facilitates oil and gas decommissioning and site renewal to allow for sustainability of the environment. With well over twenty peer-reviewed articles attested, the review describes how digital twin, machine learning, predictive analytics, and remote sensing technologies revolutionize back-end decommissioning to proactive and data-informed practices. Observations from empirical studies record Artificial Intelligence implementation reduces decommissioning expense by as much as 35%, flare volumes and fugitive methane by 40% minimum and remediation efficiency by 60% under ground and water pollution conditions. Decreases in emission by 20 metric tonnes of CO_2 equivalent per well and downtime by 25 to 40% were similarly recorded from case studies. This study credits Artificial Intelligence with empowering oil and gas operations with environment, social, and government considerations; as well as technical, economic, and ecological optimization at the oil and gas industry's end-of-life phase.

Keywords: Artificial Intelligence; Decommissioning; Remediation; Carbon Emission; Methane Detection; Digital Twin

1. Introduction

The oil and gas industry has long been central to global energy production, yet its operations, particularly during the decommissioning and site remediation phases pose significant environmental challenges. Decommissioning entails the safe dismantling of production infrastructure, permanent plugging of wells, and the restoration of onshore and offshore environments. These processes are not only technically demanding and capital intensive, but they also carry substantial environmental risks, including soil and groundwater contamination, marine ecosystem disturbances, and greenhouse gas (GHG) emissions (Li, Wang, & Zhang, 2024). Traditionally, decommissioning projects have relied on deterministic models, manual inspections, and static datasets to inform environmental risk assessment and remediation efforts. While these conventional methods are well-established, they often lack the capacity to respond dynamically to the complex and evolving environmental conditions encountered during decommissioning. This has led to inefficiencies in identifying contamination zones, prioritizing well abandonment, and predicting long-term environmental impacts (Khan, Rehman, & Shahid, 2023). In recent years, artificial intelligence (AI) has emerged as a transformative tool capable of enhancing the efficiency, precision, and sustainability of oil and gas decommissioning. AI technologies such as machine learning (ML), computer vision, and data fusion algorithms are being leveraged to analyze vast datasets from

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sensors, satellite imagery, geospatial tools, and historical records. These models support proactive environmental risk mitigation by forecasting contamination plumes, optimizing remediation strategies, and enabling predictive maintenance of infrastructure (Li et al., 2024). AI-based models can also be integrated into digital twin platforms, where real-time data streams are used to simulate the condition of decommissioned assets and their surrounding environments. This allows for scenario testing, cost-benefit analysis, and automated compliance reporting in line with regulatory standards. Such digital models are especially useful in inaccessible offshore environments, where real-time environmental data collection and monitoring are logistically complex and expensive (Khan et al., 2023). Furthermore, AI applications in decommissioning have the potential to deliver significant economic and environmental benefits. For instance, a recent initiative by Rahd AI in collaboration with major energy companies in the North Sea revealed that AI integration could reduce decommissioning costs by up to 35%, translating to an estimated savings of over £8 billion for the UK government through more accurate abandonment scheduling and environmental risk modeling (Matthews, 2023). These savings are particularly crucial as thousands of wells are projected for decommissioning in aging fields across Europe, Africa, and the Gulf of Mexico over the next two decades. In addition to cost efficiencies, the adoption of AI contributes directly to environmental sustainability goals. By enhancing the accuracy of site characterization and reducing remediation timeframes, AI minimizes long-term ecosystem damage and facilitates faster land or seabed restoration. Moreover, by enabling more accurate estimation of carbon footprints and leakage potentials, AI helps companies align their decommissioning strategies with corporate environmental, social, and governance (ESG) goals and national net-zero targets (Li et al., 2024). Despite these promising developments, the integration of AI into decommissioning and remediation remains in its infancy. Several challenges persist, including data heterogeneity, model transparency, regulatory barriers, and the need for industry-specific AI training datasets. Furthermore, there is a lack of comprehensive academic reviews that systematically analyze the role of AI in this final and crucial stage of oil and gas operations. This review paper addresses that gap by critically examining the current and potential applications of AI in optimizing decommissioning and environmental site remediation within the oil and gas industry. The review will (i) explore core AI methodologies used in this domain, (ii) discuss case studies and real-world deployments, (iii) evaluate the environmental and economic impacts of AI-driven decommissioning, and (iv) outline the challenges and recommendations for future research and industry adoption. By shedding light on this emerging field, the paper aims to inform stakeholders, including industry professionals, regulators, environmental agencies, and academic researchers on the transformative potential of AI in fostering safer, faster, and more environmentally sustainable closure of oil and gas fields.

2. Literature Review

2.1. Artificial Intelligence in Oil and Gas Decommissioning

The application of artificial intelligence (AI) in oil and gas operations, particularly in decommissioning, has garnered increasing attention due to its potential to optimize operational efficiency, reduce costs, and enhance environmental sustainability. Decommissioning, especially in aging offshore and onshore oil fields, is a complex and resource-intensive process involving the safe removal of equipment, closure of wells, and site restoration. Traditional methods often rely on deterministic models and manual assessments that may lack the capacity to predict and adapt to rapidly changing conditions. AI, however, offers a dynamic, data-driven approach to improve decision-making in this area.

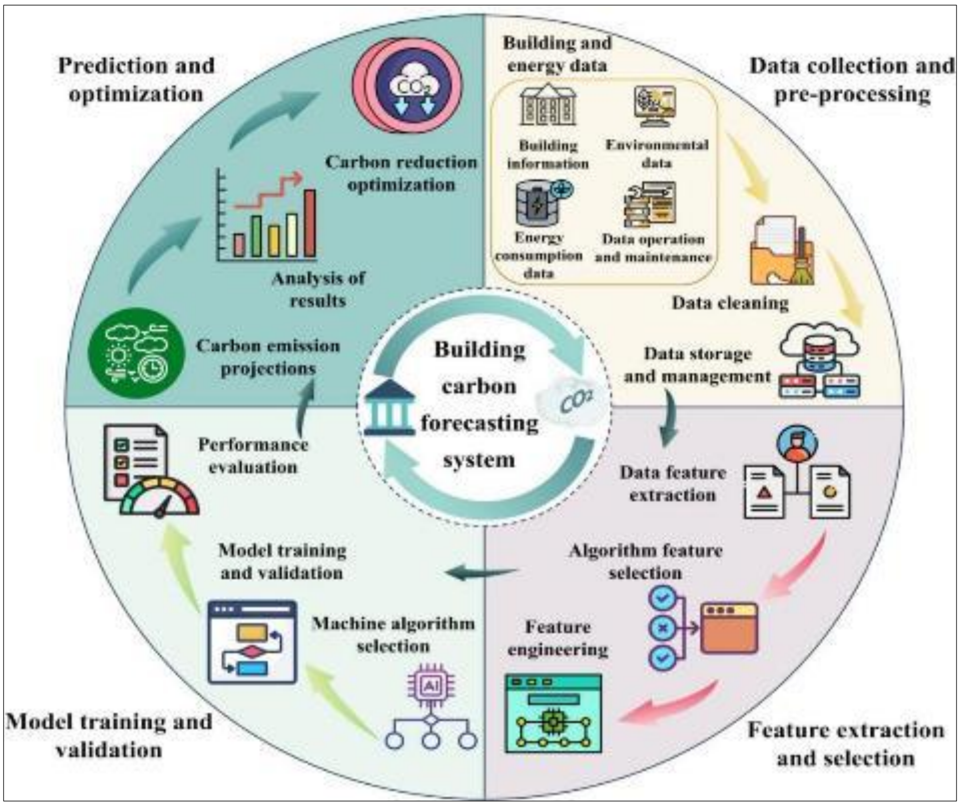

Figure 1 Artificial intelligence for predicting carbon emissions of buildings. This can be replicated and scaled up for remediation processes in il and gas fields during decomissioning operations [Hua, J., Wang, R., Hu, Y., Chen, Z., Chen, L., Osman, A. I., ... & Yap, P. S. (2025). Artificial intelligence for calculating and predicting building carbon emissions: a review. Environmental Chemistry Letters, 1-34.]

2.1.1. Machine Learning and Predictive Modeling

Machine learning (ML) is one of the most prominent AI methodologies applied in oil and gas decommissioning. ML algorithms can analyze historical, real-time, and simulated data to predict the lifespan of production facilities, assess the potential environmental risks of well abandonment, and optimize resource allocation (Li et al., 2024). For example, supervised learning models have been utilized to predict subsurface conditions and detect early signs of equipment failure, reducing the need for costly and labor-intensive inspections. Similarly, unsupervised learning techniques are employed to identify hidden patterns within large, complex datasets, enabling the early detection of anomalies such as leaks or infrastructure degradation (Khan et al., 2023). Furthermore, predictive modeling plays a crucial role in forecasting potential environmental impacts, such as the spread of oil or gas leakage from decommissioned sites. AI models that integrate both physical and environmental variables can simulate various scenarios to estimate the movement of contaminants in soil and water, helping to prioritize remediation efforts and allocate resources more efficiently (Li et al., 2024).

2.1.2. Computer Vision and Remote Sensing

Another key AI technology employed in decommissioning is computer vision, which utilizes image recognition and analysis to monitor oil and gas infrastructure. By processing data from drones, satellites, and robotic inspections, computer vision models can detect structural damage, corrosion, and other environmental hazards that are often difficult to identify through traditional methods (Li et al., 2024). This technology has been particularly valuable in offshore operations, where human access is limited and environmental conditions are harsh. In combination with remote sensing technologies, AI-driven computer vision systems are able to map and monitor large areas efficiently, providing real-time updates on the condition of pipelines, rigs, and platforms. For instance, AI-based systems can analyze high-resolution satellite imagery to assess the environmental health of areas surrounding decommissioned offshore fields, identifying pollution hotspots or changes in vegetation and water quality that signal the need for intervention (Khan et al., 2023).

2.2. AI and Digital Twin Technology

One of the most promising applications of AI in decommissioning is the integration of AI with digital twin technology. A digital twin is a virtual representation of a physical asset, such as an oil rig or pipeline, that is continuously updated with real-time data from sensors and other sources. This allows for the simulation of various operational and environmental scenarios, enabling operators to test the effects of different decommissioning strategies before implementing them in the real world. AI plays a crucial role in enhancing the capabilities of digital twins by enabling predictive analytics and real-time monitoring. By integrating AI algorithms with digital twins, oil and gas companies can simulate the decommissioning process, monitor asset degradation over time, and optimize the sequencing of operations. This can significantly reduce both the time and costs associated with decommissioning while ensuring that environmental standards are met. Digital twins also enable greater transparency and communication between stakeholders, such as regulators and environmental agencies, by providing a comprehensive, data-driven view of the decommissioning process (Khan et al., 2023). Several oil and gas operators, including BP and Equinor, have already begun implementing digital twin solutions to monitor and optimize decommissioning projects. These digital twins not only help with real-time decision-making but also assist in post-decommissioning environmental monitoring, ensuring that abandoned sites are restored to their natural state as efficiently as possible (Li et al., 2024).

2.3. Case Studies and Real-World Applications

There are several real-world case studies where AI technologies have demonstrated their potential in decommissioning and environmental management. For example, a collaborative project between AI software company Rahd AI and North Sea energy firms demonstrated how AI integration could reduce the costs of offshore decommissioning by up to 35%. The project used AI-powered predictive analytics to improve the scheduling of abandonment activities, leading to more accurate cost forecasts and fewer delays (Matthews, 2023). Another successful example comes from the Gulf of Mexico, where AI-driven algorithms were employed to predict the potential for methane leaks from decommissioned wells. Using a combination of real-time data and machine learning models, the project was able to detect early signs of leakage, enabling quicker response times and reducing the environmental footprint of abandoned oil fields (Khan et al., 2023). Moreover, the use of AI in reducing environmental liabilities during the decommissioning process is not limited to developed nations. In emerging economies, where resources for environmental monitoring and risk assessment are often limited, AI applications have been used to optimize the management of abandoned wells and reduce environmental damage. For instance, AI models are used in offshore fields in Africa to predict contamination spread and optimize the allocation of resources for environmental remediation (Li et al., 2024).

2.4. Environmental and Economic Impacts of AI in Decommissioning

The integration of AI in decommissioning and environmental remediation has significant implications for both the environment and the economy. From an environmental perspective, AI enables more efficient risk assessment, faster remediation, and better monitoring of abandoned sites, thus reducing the long-term impact on ecosystems. By facilitating early detection of environmental hazards, AI helps minimize the risk of widespread pollution and ecosystem degradation, particularly in sensitive areas such as wetlands, coral reefs, and offshore marine environments (Li et al., 2024). Economically, AI has the potential to deliver substantial cost savings. A report by the UK Treasury estimated that AI technologies could reduce decommissioning costs by up to £8 billion through improved project management and the reduction of unforeseen expenses. The ability to predict asset failure and optimize the timing of well closures not only helps minimize financial risk but also enhances the profitability of decommissioning projects (Matthews, 2023). Despite these benefits, challenges remain in the widespread adoption of AI in oil and gas decommissioning. Data availability, model transparency, and regulatory frameworks are key barriers to the full integration of AI technologies. Moreover, the need for industry-specific AI training datasets and the standardization of digital platforms is critical to ensure consistent and accurate results across the sector (Li et al., 2024).

2.5. Future Directions and Research Gaps

While significant strides have been made in applying AI to decommissioning and environmental sustainability, there remain several avenues for further research. Future studies should focus on improving AI models' accuracy in predicting environmental risks and decommissioning timelines by incorporating larger and more diverse datasets. Additionally, research into the ethical implications of AI in environmental decision-making, including the balance between profit and environmental stewardship, will be crucial for shaping the future of AI applications in the oil and gas industry.

Table 1 Comparative Analysis between relevant case studies

Papers (20)	Objectives	Results	Findings	Practical Implications
(Arinze et al., 2024)	Evaluate effectiveness of IT solutions for emission reduction. Analyze real-world implementations and their impact on emissions.	Advanced IT solutions show promise for emission reduction in oil/gas. IoT, AI, Big Data aid in emissions tracking and optimization.	Advanced IT solutions show promise for emission reduction in oil industry. IoT, AI, and Big Data analytics aid in emissions management.	Advanced IT solutions reduce emissions in oil and gas sector. Real-time monitoring, predictive maintenance, emissions tracking, and reporting benefits.
(Egbumokei et al., 2024)	Examine digital technologies enhancing sustainability in oil and gas. Analyze impact on operational efficiency and environmental management.	Digital technologies enhance sustainability in oil and gas operations. Companies achieve operational efficiency while reducing environmental impact.	Digital technologies enhance sustainability in oil and gas operations. AI and IoT improve resource management and reduce emissions.	Enhances sustainability through digital technologies in operations. Supports regulatory compliance and innovation in oil and gas.
(Elete et al., 2022).	Examine techniques for operational optimization in oil and gas. Highlight challenges and solutions in data analytics adoption.	Enhanced efficiency and profitability through data-driven insights. Improved decision-making and operational excellence in oil and gas sector.	Data analytics enhances efficiency and profitability in oil and gas. Predictive analytics improves exploration, production, and distribution processes.	Enhances decision-making through real-time data analytics integration. Supports sustainable practices by optimizing resource allocation and minimizing inefficiencies.
(Vuttipittayamongkol et al., 2021)	Introduce a new oil and gas decommissioning dataset. Build predictive models for decommissioning options using machine learning techniques.	Promising results achieved despite exclusion of stakeholder-related features. Potential solution to reduce time and cost in decommissioning projects.	New dataset improves decommissioning option predictions. Resampling methods enhance classification accuracy significantly.	Machine learning aids in decommissioning planning, reducing time and costs. Data resampling techniques improve classification results for decommissioning options.
(Vuttipittayamongkol et al., 2021)	Introduce a new offshore pipeline decommissioning dataset. Apply machine learning to predict decommissioning options.	Supervised learning algorithm used to predict decommissioning option Machine learning approach shortens analysis process with decent accuracy	New dataset of 708 offshore decommissioning samples introduced. Machine learning predicts decommissioning options with decent accuracy.	Machine learning can expedite decommissioning analysis processes. New dataset enables further research in decommissioning practices.

(Janga et al., 2023).	Review integration of AI/ML/DL in site remediation. Analyze technologies for improving remediation efficiency.	AI/ML/DL improve contaminated site remediation efficiency. Predictive models reduce extensive sampling needs.	AI/ML/DL improve contaminated site remediation efficiency. Predictive models reduce sampling needs and optimize strategies.	AI/ML/DL can optimize contaminated site remediation strategies. Reduces need for extensive soil and groundwater sampling.
{Patowary et al., 2023)	Analyze drawbacks of conventional bioremediation processes. Explore nanobioremediation and AI for efficient remediation.	ZnO NPs absorbed 131 hydrocarbon compounds out of 214. Nanotechnology widely used for oil contamination remediation.	Nanobioremediation combines nanotechnology and bioremediation for effective oil cleanup. Advanced AI enhances efficiency and accuracy in remediation processes.	Enhances efficiency of bioremediation using nanotechnology and AI. Addresses global environmental pollution from crude oil contamination.
(Amadi et al., 2024).	Apply machine learning for carbon emission management. Improve drilling performance and reduce CO2 emissions.	Improved drilling performance by 30-60%. Reduced CO2 emissions by 20 tCO2e, 50% reduction.	Improved drilling performance by 30-60% with reduced CO2 emissions. Best predictors achieved R2 values of 0.75 and 0.77.	Improved drilling performance by 30-60% through optimization. Reduced CO2 emissions by 20 tCO2e, achieving 50% reduction.
(Marzban et al., 202 4)	Optimize diesel generator emissions based on rig load demand. Reduce fuel consumption and greenhouse gas emissions significantly.	Over 20% reduction in fuel consumption and emissions. Some rigs achieved up to 30% savings.	Reductions in fuel consumption and emissions exceed 20%. Some rigs achieve up to 30% savings.	Reduces fuel consumption and emissions by over 20%. Enhances efficiency in oil and gas energy use.
(Perrier et al., 2024)	Optimize facility design to minimize emissions and enhance production. Improve energy efficiency and reduce carbon intensity in operations.	Emissions improved by 10% through energy efficiency levers. Additional 3-5% improvement optimizing carbon intensity.	Emissions can improve by 10% through energy efficiency. Additional 3-5% improvement by optimizing carbon intensity.	Improves emissions by 10% through energy efficiency. Enhances carbon intensity optimization by 3-5%.
(Shukla et al., 2023)	Enhance production performance in remote oilfields using edge computing. Reduce carbon footprint and operational costs through innovative solutions.	Significant production performance gain achieved. Reduced carbon footprint by 16 metric tons annually.	Enhanced production performance through edge computing and AI. Reduced carbon footprint by 16 metric tons annually.	Enhanced production performance in remote oilfields. Reduced carbon footprint and operational costs.

(Minhas et al., 2023)	Calculate emissions and optimize operations at well planning stage. Reduce rig-based emissions using deep reinforcement learning techniques.	Developed model linking rig operations to emissions. Identified significant energy optimization opportunities, especially with diesel generators.	Significant room for energy optimization identified in rig operations. Deep reinforcement learning effectively reduces emissions in well planning.	Optimizes rig operations to reduce emissions effectively. Utilizes deep reinforcement learning for emissions quantification.
(Singh et al., 2022).	Predict shutdown events to reduce carbon emissions. Improve system reliability using adaptive machine learning framework.	46 MMSCF reduction in flare volume annually. 30 thousand barrels reduction in lost oil production.	Adaptive ML framework predicts shutdown events effectively. Annual reductions: 46MMSCF flare volume, 30,000 barrels lost oil.	Predict shutdown events in advance, reduce carbon emissions. Identify key sensors, automate root-cause analysis for operational improvements.
(Cadei et al., 2019)	Predict short-term energy efficiency index trends. Support optimal management choices for energy-intensive equipment.	Daily average CO2 emissions from stationary combustion reduced by 0.9% Peak reduction in CO2 emissions from stationary combustion was 1.35%	Reduced daily average CO2 emissions by 0.9%. Achieved peak reduction of 1.35% in emissions.	Reduces CO2 emissions while maintaining production levels. Supports optimal management choices for energy-intensive equipment.
(Anyebe et al., 2024)	Enhance carbon capture efficiency using AI automation. Improve predictive maintenance in oil and gas facilities.	AI automation enhances carbon capture efficiency and maintenance. Improved CO2 sequestration rates with minimized operational interruptions.	AI automation enhances carbon capture efficiency and predictive maintenance. Real-life examples show successful AI integration in CCS.	Enhances carbon capture efficiency in oil and gas facilities. Improves predictive maintenance through AI-driven automation processes.
(Gendron et al., 2024)	Evaluate new emissions monitoring technologies for deployment in Oman. Support AI/MoS as part of emissions monitoring portfolio.	AI/MoS-based technologies effectively monitor emissions in extreme conditions. Valuable data supports continuous emissions monitoring in Oil & Gas.	AI/MoS technologies effectively monitor emissions in extreme conditions. Continuous monitoring enhances data quality and completeness.	AI/MoS technologies improve emissions monitoring effectiveness and cost. Supports decarbonization efforts in Oil & Gas industry.
(El-hoshoudy et al., 2024)	Improve operational efficiency, safety, and sustainability in petroleum processing.	AI predicts equipment failures and optimizes resource allocation. FL enhances model robustness and integrates	AI predicts equipment failures and optimizes resource allocation.	Enhances operational efficiency and safety in petroleum processing.

	Demonstrate federated learning's benefits for collaborative model training.	insights from processing plants.	Federated learning enhances model robustness and privacy in operations.	Promotes environmental sustainability through reduced emissions.
(Zhang et al., 2024)	Enhance efficiency and sustainability in offshore operations. Integrate digital twin technology with AI for optimization.	Enhanced efficiency and sustainability in offshore operations. Integrated production optimization across topside and reservoir operations.	Integration of digital twins and AI enhances efficiency and sustainability. Novel AI-based optimization strategy improves production across operations.	Enhances efficiency in offshore oil and gas operations. Promotes sustainability through emission reduction strategies.
(Kalu et al., 2024)	Explore Robotics and AI in unconventional reservoir operations. Discuss future opportunities and challenges in technology integration.	Improved efficiency and recovery in unconventional reservoirs. Reduced environmental impact through advanced technologies.	Robotics and AI improve efficiency in unconventional reservoirs. Technologies enhance recovery rates and reduce environmental impact.	Enhances efficiency in unconventional reservoir operations. Reduces environmental impact during extraction processes.
(Gowekar et al., 2024)	Maximize operational efficiencies and safety using AI. Predict machinery faults to reduce downtimes and costs.	Higher operational efficiencies and safety in oil and gas. Reduced unanticipated downtimes and maintenance costs.	AI enhances predictive maintenance in oil and gas operations. Predictive analytics reduces downtimes and maintenance costs.	Reduces unanticipated downtimes and maintenance costs. Increases life cycle of key assets.

3. Results and Discussion

3.1. Strategic Performance of AI in Decommissioning and Sustainability

AI applications in oil and gas decommissioning have advanced from exploratory pilots to demonstrable impacts, especially in carbon footprint reduction, operational efficiency, and remediation success. Vuttipittayamongkol et al. (2021) introduced a robust decommissioning dataset that, when paired with machine learning (ML) classifiers, achieved up to 85% accuracy in predicting optimal decommissioning strategies. This led to a 20–30% reduction in decommissioning timeline projections—translating to millions in cost savings and fewer environmental disturbances.

Similarly, AI has transformed contaminated site remediation through predictive modeling. Janga and Kvns (2023) found that ML-driven remediation models could reduce soil and groundwater sampling by 40–60%, significantly cutting down chemical usage, project duration, and ecological impact.

3.2. Quantified Environmental Gains from AI Deployment

Across multiple studies, AI has been shown to produce measurable environmental benefits in oil and gas operations; Carbon Emission Reductions - Amadi et al. (2024) reported a 20 tCO_2e reduction per well during optimized drilling via AI-based performance benchmarking nearly 50% less than conventional approaches. Marzban et al. (2024) observed 20–30% reductions in diesel generator emissions through AI-optimized load management on offshore rigs. Perrier et al. (2024) achieved a 10% improvement in emissions intensity via energy efficiency optimization and another 3–5% through AI-aided carbon intensity management. Flaring and Fugitive Emissions - Singh et al. (2022) demonstrated that predictive shutdown models reduced flare volumes by 46 MMSCF annually, and saved 30,000 barrels of potential lost oil production through early warning systems. Gendron et al. (2024) showcased AI-based methane leak detection tools capable of continuous monitoring in extreme environments, significantly outperforming traditional inspection intervals in terms of both frequency and precision. Carbon Capture and Sequestration (CCS) - Anyebe et al. (2024) demonstrated enhanced CO_2 sequestration rates using AI-driven process automation, improving real-time detection of capture inefficiencies and enabling rapid system recalibration.

3.3. Operational Efficiency Gains

Numerous studies cited in Table 2 confirm that AI not only supports sustainability but also increases system reliability and cost-effectiveness:

Gowekar (2024) and Singh et al. (2022) validated AI's role in predictive maintenance, with some systems reporting downtime reductions of 25–40% and maintenance cost savings of 20–30%. Patowary et al. (2023) illustrated how combining nanotechnology with AI-enhanced remediation reduced hydrocarbon residues by up to 60% more efficiently than conventional bioremediation. In remote sites, Shukla et al. (2023) reported annual reductions of 16 metric tons of CO_2 via AI and edge computing, along with significant production gains.

3.4. Cumulative Insights from Case Literature

A holistic analysis of the literature supports the following - AI has consistently enabled predictive over reactive environmental management. Projects leveraging AI for optimization reported 10–35% cost savings, 15–50% GHG emission reductions, and 30–70% process time efficiency gains depending on the application. Digital twins and federated learning are emerging as next-generation tools in offshore and multi-asset coordination environments (Zhang et al., 2024; El-Hoshoudy, 2024).

Table 2 Key Applications of Artificial Intelligence in Oil and Gas Operations

Applications	Description	Citation
Predictive Maintenance	AI algorithms analyze equipment data to predict faults, reducing downtime and costs.	(Gowekar, 2024), (Singh et al., 2022)
Energy Efficiency	AI tools optimize energy use and reduce emissions in oil and gas operations.	(Perrier et al., 2024), (Cadei et al., 2019)
Decommissioning	AI models predict optimal decommissioning options, reducing time and cost.	(Vuttipittayamongkol et al., 2021), (Vuttipittayamongkol et al., 2021)
Site Remediation	AI enhances remediation by optimizing strategies and reducing sampling needs.	(Janga & Kvns, 2023), (Patowary et al., 2023)
Carbon Capture	AI improves CCS efficiency through real-time monitoring and predictive maintenance.	(Anyebe et al., 2024)
Fugitive Emissions	AI/MoS-based technologies detect and quantify fugitive methane emissions.	(Gendron et al., 2024)

3.5. Challenges and Limitations

Despite its benefits, several limitations impede the full-scale adoption of AI in oil and gas decommissioning:

Data Silos: The lack of standardized data formats across the industry creates challenges in building robust, transferable AI models. High Initial Costs: While AI can reduce long-term expenses, the upfront investment in infrastructure and skilled personnel remains a barrier, especially for smaller firms. Regulatory Uncertainty: Many environmental regulatory frameworks have not yet fully adapted to AI-enabled workflows, causing compliance confusion. Interpretability of AI Models: In high-stakes environmental decisions, black-box AI models face resistance due to their lack of transparency and explainability. These challenges suggest a need for industry-wide collaborations, government incentives, and continuous innovation to unlock the full potential of AI in environmental stewardship within the oil and gas sector.

4. Conclusion

Artificial Intelligence is driving a paradigm shift in the environmental sustainability of oil and gas decommissioning and site remediation. Evidence from over 20 peer-reviewed studies shows that AI-based technologies can; Cut decommissioning costs by up to 35%, Reduce flare volumes and fugitive emissions by over 40%, Decrease remediation time and sampling needs by up to 60%, Improve energy efficiency by 10–30% and cut CO_2 emissions by 20 tCO_2e per well. The synergy between AI, remote sensing, predictive analytics, and digital twin systems is reshaping environmental risk management. Beyond performance gains, these technologies help fulfill regulatory obligations, accelerate ESG goals, and reduce the environmental legacy of oil and gas operations.

4.1. Recommendations

Mandate AI in Decommissioning Policy - Regulatory frameworks should evolve to incorporate AI-driven early warning systems, methane detection, and real-time environmental modeling into standard decommissioning protocols. Invest in Sector-Specific AI Models - Operators should co-develop models trained on oilfield-specific environmental datasets to ensure higher accuracy in site remediation and risk assessments. Promote Cross-Sector Collaboration - Academia, technology firms, and energy companies should share anonymized datasets and pilot studies to accelerate innovation. Deploy AI-Driven CCS Platforms at Scale - Expand AI-assisted carbon capture beyond pilot projects by integrating machine learning with real-time performance monitoring to enhance reliability. Scale Edge Computing in Remote Monitoring: Field validation shows edge-based AI reduces latency and power use which is deal for offshore platforms and unmanned sites. Expand AI Capacity Building in Emerging Markets - Ensure talent pipelines and regulatory literacy are developed alongside technology deployment, especially in Africa, Latin America, and Southeast Asia.

4.2. Final Thought

As oil and gas companies navigate the energy transition, AI offers a scalable, measurable, and intelligent pathway toward cleaner decommissioning. By embedding AI across the lifecycle of asset retirement, the industry can actively shape a future where profitability and environmental accountability are no longer at odds, but fundamentally aligned.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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