JOURNAL OF GAS TECHNOLOGY

Volume 10 / Issue 2 / Winter 2025 / Pages 88-118

Journal Home page: https://jgt.irangi.org

Intelligent and Circular Drilling Wastewater Treatment: A Review Integrating Machine Learning, Uncertainty Quantification, and Resource Recovery

Seyed Ata Elyas Sorkhabi[1], Mohammadreza Akbari[2*], Yasin Khalili[3]

1. BSc. Student, Department of Petroleum and Geoenergy Engineering, Amirkabir University of Technology, Tehran, Iran
2. Assistant Professor, Department of Petroleum and Geoenergy Engineering, Amirkabir University of Technology, Tehran, Iran
3. Ph.D. Student, Department of Petroleum and Geoenergy Engineering, Amirkabir University of Technology, Tehran, Iran

ARTICLE INFO

REVIEW ARTICLE

Article History:
Received: 27 October 2025
Revised: 01 November 2025
Accepted: 11 December 2025

Keywords:
Drilling wastewater treatment
Machine learning
Uncertainty quantification
Circular economy
Resource recovery
Oil and gas industry

DOR: 20.1001.1/jgt.2026.2082269.1066

ABSTRACT

Drilling wastewater generated during oil and gas operations presents a complex environmental challenge due to its highly variable composition, large volumes, and the presence of hazardous organic and inorganic contaminants. Conventional treatment approaches, although widely implemented, often fail to achieve consistent performance under dynamic operating conditions and increasingly stringent environmental regulations.

This review provides a comprehensive and forward-looking analysis of drilling wastewater management by integrating treatment technologies with emerging concepts of circular economy, data-driven intelligence, and uncertainty quantification. The characteristics and sources of drilling wastewater are examined to highlight their inherent variability and associated treatment challenges. Conventional, advanced, and hybrid treatment technologies are critically evaluated in terms of efficiency, limitations, and applicability for water reuse and resource recovery. Circular economy strategies, including water recycling, material recovery, and zero liquid discharge (ZLD), are also assessed from a sustainability perspective.

In addition, the role of machine learning in performance prediction, process optimization, and real-time monitoring is discussed, alongside uncertainty quantification approaches such as probabilistic modeling and Bayesian inference for risk-informed decision-making. From an industrial perspective, the integration of intelligent modeling and uncertainty-aware frameworks enables more reliable, adaptive, and efficient treatment systems.

Despite these advancements, challenges remain in data availability, model transferability, system integration, and economic feasibility. This review establishes a unified framework that bridges environmental engineering, data science, and sustainability, providing a pathway toward intelligent, circular, and resilient drilling wastewater treatment systems.

How to cite this article
S.A.E. Sorkhabi, M. Akbari, Y. Khalili, Intelligent and Circular Drilling Wastewater Treatment: A Review Integrating Machine Learning, Uncertainty Quantification, and Resource Recovery. Journal of Gas Technology. 2025; 10(2): 88-118. (https://jgt.irangi.org/article_737844.html)

* Corresponding author.
E-mail address: akbari.pe@aut.ac.ir, (M. Akbari).

Available online 30 December 2025

1. Introduction

Drilling wastewater management has become a critical component of upstream oil and gas operations due to increasingly complex environmental, operational, and regulatory challenges associated with drilling activities (Lebedev and Cherepovitsyn 2024). As exploration expands toward deeper, geologically heterogeneous, and environmentally sensitive regions, large volumes of wastewater containing drilling fluids, cuttings, formation water, and chemical additives are generated. These waste streams pose significant risks to soil, surface water, and groundwater systems if not properly treated. In response, regulatory agencies worldwide have introduced stricter discharge limits, zero-pollution policies, and reporting requirements, compelling operators to adopt more reliable and sustainable wastewater management practices (Adverse).

Drilling wastewater is inherently complex and dynamic, with composition varying continuously depending on geological formations, drilling fluid formulations, and operational conditions. Conventional treatment approaches primarily based on physical, chemical, and biological processes have been widely applied; however, they often rely on fixed design assumptions and are not well-suited to handle such variability (Tsolakis, Harrington et al. 2023). As a result, treatment performance can be inconsistent, particularly under fluctuating field conditions.

Conventional review studies on drilling wastewater treatment are typically based on static, technology-centric assessments, in which treatment processes are described under fixed assumptions and idealized conditions. In this context, the term static refers to approaches that do not explicitly account for temporal variability, fluctuations in wastewater composition, or changes in operational conditions. As a result, such assessments often overlook the dynamic behavior of real systems and provide limited insight into how treatment performance evolves over time (Ghasemi, Akbari et al. 2025).

In contrast, drilling wastewater systems are inherently dynamic, characterized by continuously changing composition, flow rates, and physicochemical properties due to variations in geological formations, drilling phases, and operational practices. A dynamic approach therefore refers to systems that evolve over time and incorporate real-time data, adaptive modeling, and feedback-driven control mechanisms. These approaches enable continuous adjustment of treatment processes in response to changing inputs, improving accuracy, efficiency, and robustness (Yang, Diao et al. 2022).

Consequently, modern wastewater management requires an integrated and dynamic framework that combines real-time monitoring, data-driven intelligence, and uncertainty-aware modeling. The growing application of machine learning, advanced sensing technologies, and probabilistic methods reflects this shift toward adaptive systems capable of capturing variability and supporting more reliable and optimized treatment performance (Smol, Adam et al. 2020, Matheri, Mohamed et al. 2022, Zong and Guan 2025).

In parallel, the transition from linear waste disposal toward circular economy principles has introduced new opportunities for sustainable wastewater management. Circular approaches emphasize water reuse, resource recovery, and waste minimization, transforming drilling wastewater from an environmental liability into a potential resource. Strategies such as recovery of hydrocarbons, recycling of drilling materials, and implementation of zero liquid discharge (ZLD) systems contribute to reducing environmental impact while improving economic efficiency. ZLD refers to a treatment approach in which all wastewater is processed to eliminate liquid discharge, leaving only solid residues and enabling maximum water recovery (Scheidt, Li et al. 2018).

Another critical aspect of modern wastewater management is uncertainty quantification, which addresses the inherent variability and unpredictability of drilling wastewater systems. Variations in composition, operational conditions, and treatment performance introduce significant uncertainty that cannot be adequately captured by deterministic models. Probabilistic approaches, including Bayesian inference and Monte Carlo simulation, provide a more realistic framework for evaluating system performance, assessing risks, and supporting decision-making under uncertain conditions.

Despite recent advancements, existing review studies often treat treatment technologies, machine learning applications, circular economy strategies, and uncertainty quantification as separate domains. There remains a lack of integrated frameworks that simultaneously address these interrelated aspects. Unlike previous reviews that focus primarily on individual technologies or isolated optimization methods, this study integrates machine learning, uncertainty quantification, and circular economy principles into a unified framework. This integrated perspective enables a more realistic representation of drilling wastewater systems, where variability, data-driven intelligence, and resource recovery must be addressed collectively.

To highlight the contribution of this work in relation to existing literature, a comparative summary of recent studies is provided in Table 1. The table outlines differences in scope, methodology, and level of integration, emphasizing the unique contribution of the present study in combining treatment technologies with intelligent and uncertainty-aware approaches.

This review adopts a structured and transparent methodology to ensure comprehensive coverage and scientific rigor. Peer-reviewed publications were collected from major scientific databases, with particular emphasis on recent studies (2022-2025) to capture the latest developments in treatment technologies, machine learning applications, and circular economy strategies.

Overall, this work provides a holistic and forward-looking framework for drilling wastewater management that integrates engineering, data science, and sustainability principles. By combining treatment technologies, intelligent modeling, uncertainty quantification, and circular economy concepts, the study aims to support the development of adaptive, efficient, and environmentally responsible wastewater treatment systems for the oil and gas industry.

(Table 1) presents a comparative overview of recent studies, highlighting their methodologies, key contributions, and limitations, and demonstrating how the present study addresses existing gaps through an integrated framework combining machine learning, uncertainty quantification, and circular economy principles.

Table 1. Comparative Summary of Recent Studies on Drilling Wastewater Treatment Technologies and Approaches

Study (Author, Year)	Scope	Methods/ Approach	Key Contribution	Limitations	Gap Addresse in This Study
(Wei, Zhang et al. 2019)	Oilfield wastewater treatment technologies	Review of physical, chemical, and membrane processes	Highlighted efficiency of hybrid systems for complex wastewater	Limited integration of data-driven optimization	This study integrates ML and adaptive modeling for optimization
(Chang, Lee et al. 2019)	Me brane-based treatment of oily wastewater	Experimental + modeling	Demonstrated high removal efficiency of UF/ RO systems	Membrane fouling and high energy demand	Incorporates predictive maintenance and ML-based fouling prediction
(Smol, Adam et al. 2020)	Circular economy in wastewater systems	Conceptual + policy framework	Emphasized transition to resource recovery and reuse systems	Limited application to drilling wastewater specifically	Applies circular economy specifically to drilling wastewater systems
(Lawan, Kumar et al. 2023)	Advanced wastewater treatment technologies	Comprehensive review	Identified need for integration of advanced oxidation and hybrid processes	Lack of real-time operational analysis	Introduces real-time monitoring and AI-driven control
(Fernandes, Ramísio et al. 2024)	Characteristics and treatment challenges of drilling wastewater	Experimental + analytical	Provided detailed characterization of wastewater variability	Limited predictive modeling capability	Integrates ML to handle variability and prediction
(Gangwar, Rawat et al. 2025)	Environmental impacts of oilfield wastewater	Life cycle and environmental analysis	Assessed environmental risks an treatment impacts	Limited focus on optimization and adaptive systems	Combines LCA with ML and decision-support frameworks
(Zhang 2025)	Circular economy approaches	Conceptual + case studies	Proposed resource recovery pathways for wastewater reuse	Lack of real-time system integration	Integrates circular economy with intelligent control systems
(Dhadumia, Paul et al. 2026)	Hybrid treatment systems	Experimental (membrane + chemical)	Demonstrated improved contaminant removal efficiency	High cost and system complexity	Applies ML for system optimization and cost reduction
Recent Advances	AI-driven and digital wastewater systems	Digital twin, IoT, and ML integration	Demonstrated potential of autonomous and adaptive treatment systems	Data scarcity and integration challenges	Proposes unified framework combining ML, UQ, and circular economy

(Figure 1) illustrates the overall system architecture linking drilling wastewater characteristics with treatment processes, machine learning-based monitoring, uncertainty quantification, and decision-making pathways, including water reuse, resource recovery, and zero liquid discharge (ZLD).

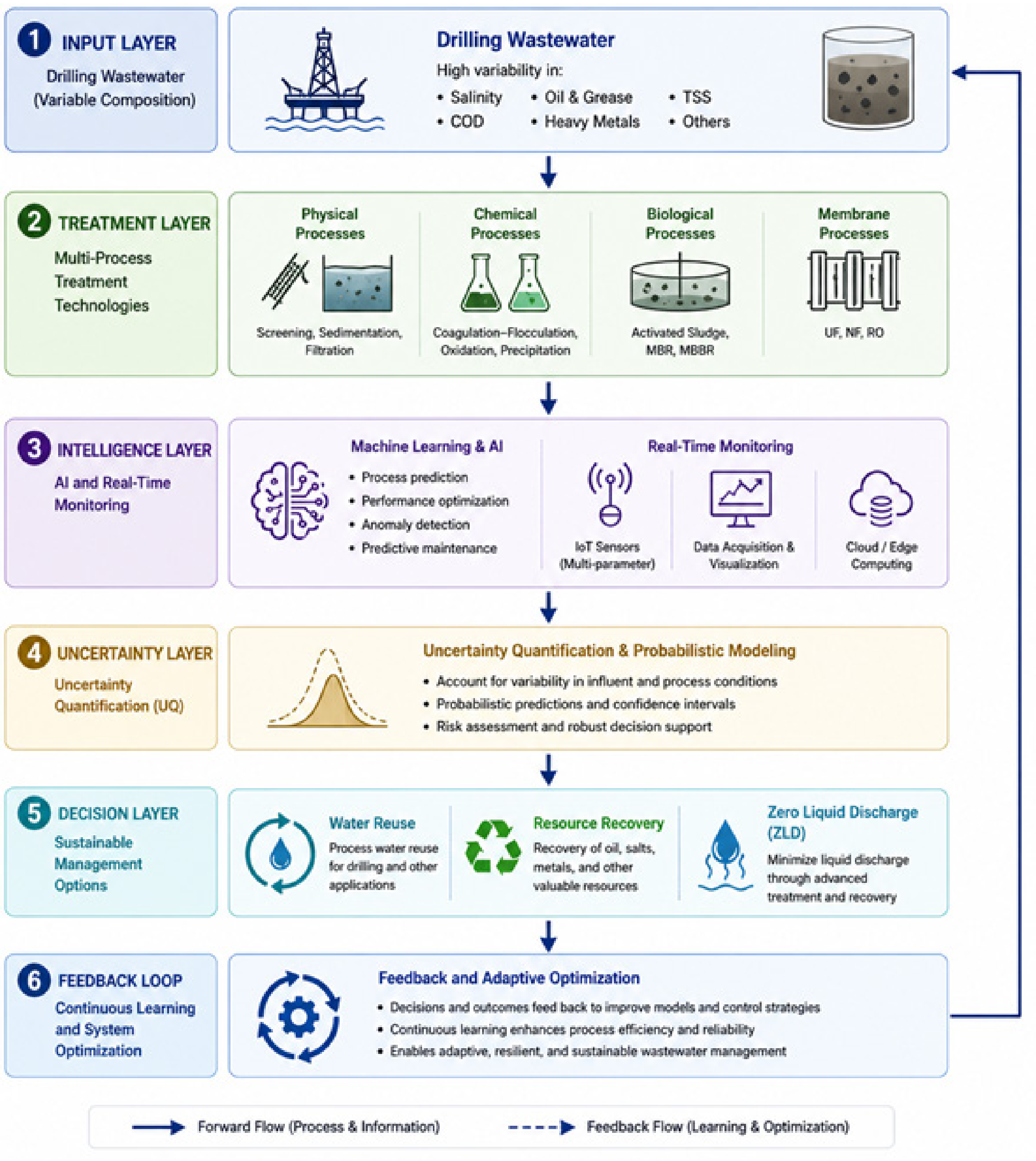

Figure 1. Integrated Framework for Intelligent and Circular Drilling Wastewater Treatment

2. Characteristics of Drilling Wastewater

Drilling wastewater is a highly complex and heterogeneous mixture whose composition varies significantly depending on the type of drilling fluid used, geological formation characteristics, operational practices, and the stage of drilling (Pereira, Sad et al. 2022, Basu, Shaw et al. 2025). Fundamentally, the wastewater derives from both water-based and oil-based drilling muds, each contributing distinct chemical and physical attributes to the waste stream (Zhang, Li et al. 2024). Water-based muds typically introduce bentonite, barite, polymers, and various inorganic salts, whereas oil-based muds contribute emulsified hydrocarbons, synthetic base oils, surfactants, and stabilizing agents, resulting in a wastewater matrix with elevated oil content and more persistent organic compounds. This duality creates substantial variability in wastewater behavior, treatment difficulty, and environmental impact, requiring tailored mitigation strategies for different operational contexts (Ahmed, Alsaihati et al. 2021).

Beyond mud-related constituents, drilling wastewater often contains a suite of hazardous and potentially toxic contaminants derived from both the formation and the drilling process itself. These include heavy metals such as chromium, cadmium, lead, arsenic, and barium, which may leach from formations or be introduced through additives. Additionally, the wastewater can contain high concentrations of dissolved solids, suspended clay particles, nitrogenous compounds, biocides, corrosion inhibitors, lubricants, and degradation byproducts of drilling chemicals. The combination of organic and inorganic pollutants many of which exhibit low biodegradability, high mobility, or strong affinity for particulates complicates separation and treatment processes. Moreover, the presence of hydrocarbons, surfactants, and emulsifiers often leads to the formation of stable oil-water emulsions that resist conventional treatment methods such as simple gravity separation or basic chemical coagulation (Barcelona, Gibb et al. 1983).

A further challenge associated with drilling wastewater is the lack of standardization in both its composition and in reporting practices across different operators and regions. Variability in drilling technology, fluid formulation, geological strata, and regulatory frameworks results in wastewater profiles that are difficult to compare or generalize (Zhang, Xu et al. 2022). For example, wastewater generated in shale gas basins may carry high levels of dissolved salts and formation minerals, whereas

Offshore drilling operations often exhibit elevated hydrocarbon content and synthetic additives due to the widespread use of oil-based and synthetic-based drilling muds in these environments. These fluids are preferred in offshore operations because they provide enhanced wellbore stability, improved lubrication, and better performance under high-pressure and high-temperature conditions. However, their use results in wastewater streams enriched with emulsified hydrocarbons, base oils, and chemically stabilized additives that are more persistent and difficult to treat (Loss, Cavali et al. 2026).

In addition, stricter operational requirements in offshore drilling, such as preventing formation damage and maintaining drilling efficiency, further drive the use of such complex fluid systems.

Overall, drilling wastewater represents a multifaceted environmental challenge characterized by chemical complexity, operational variability, and analytical uncertainty. These characteristics underscore the need for flexible, adaptive, and intelligent treatment frameworks capable of addressing both expected and unforeseen variations in wastewater composition (Garg, Kumari et al. 2024).

(Table 2) summarizes the physical, chemical, and operational characteristics of drilling wastewater, highlighting the wide variability in composition that complicates treatment design and performance prediction.

(Figure 2). Composition and variability of drilling wastewater derived from water-based and oil-based drilling muds, highlighting the diversity of suspended solids, hydrocarbons, salts, surfactants, polymers, heavy metals, and chemical additives that contribute to compositional uncertainty across formations and drilling stages.

(Figure 3). Characteristics and variability of drilling wastewater originating from water-based and oil-based drilling muds, illustrating the diverse chemical additives and contaminants present, as well as the dynamic variability in key parameters such as salinity, pH, total suspended solids (TSS), and sludge content across drilling stages and formations.

Table 2. Typical Characteristics of Drilling Wastewater
(Thacker, Carlton Jr et al. 2015, Jin, Zhang et al. 2022, Pereira, Sad et al. 2022)

	Typical Components	Concentration Range	Primary Source	Environmental Concern
Physical	Total Suspended Solids (TSS), turbidity, oil droplets	TSS: 1,000-50,000 mg/L; Oil droplets: 50-5,000 mg/L	Drill cuttings, drilling mud	Limited integration of data-driven optimization
Chemical (Inorganic)	Salts (Na^+, Cl^-), Ba, Cr, Pb	TDS: 5,000-200,000 mg/L; Heavy metals: 0.1-100 mg/L	Formation fluids, additives	Membrane fouling and high energy demand
Chemical (Organic)	Hydrocarbons, surfactants, additives	Oil & grease: 100-10,000 mg/L; COD: 500-20,000 mg/L	Oil-based muds, synthetic additives	Limited application to drilling wastewater specifically
Operational Variability	pH, salinity, temperature	pH: 10-6; Salinity: 200,000-5,000 mg/L; Temperature: 90-20C	Drilling phase, geological formation	Treatment instability, process inefficiency

Ranges are indicative and may vary depending on geological formation and drilling conditions

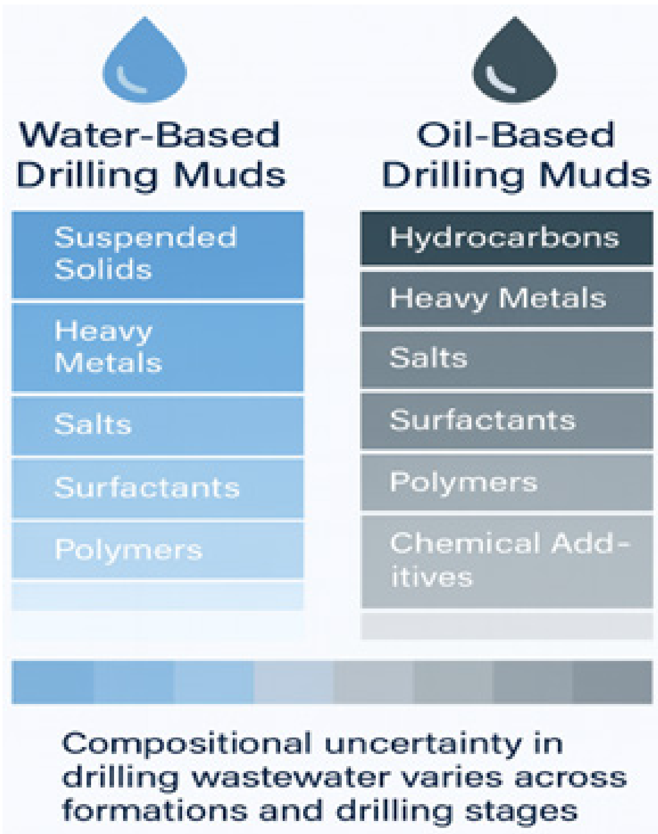

Figure 2. Composition and Variability of Drilling Wastewater from Water-based and Oil-based Muds

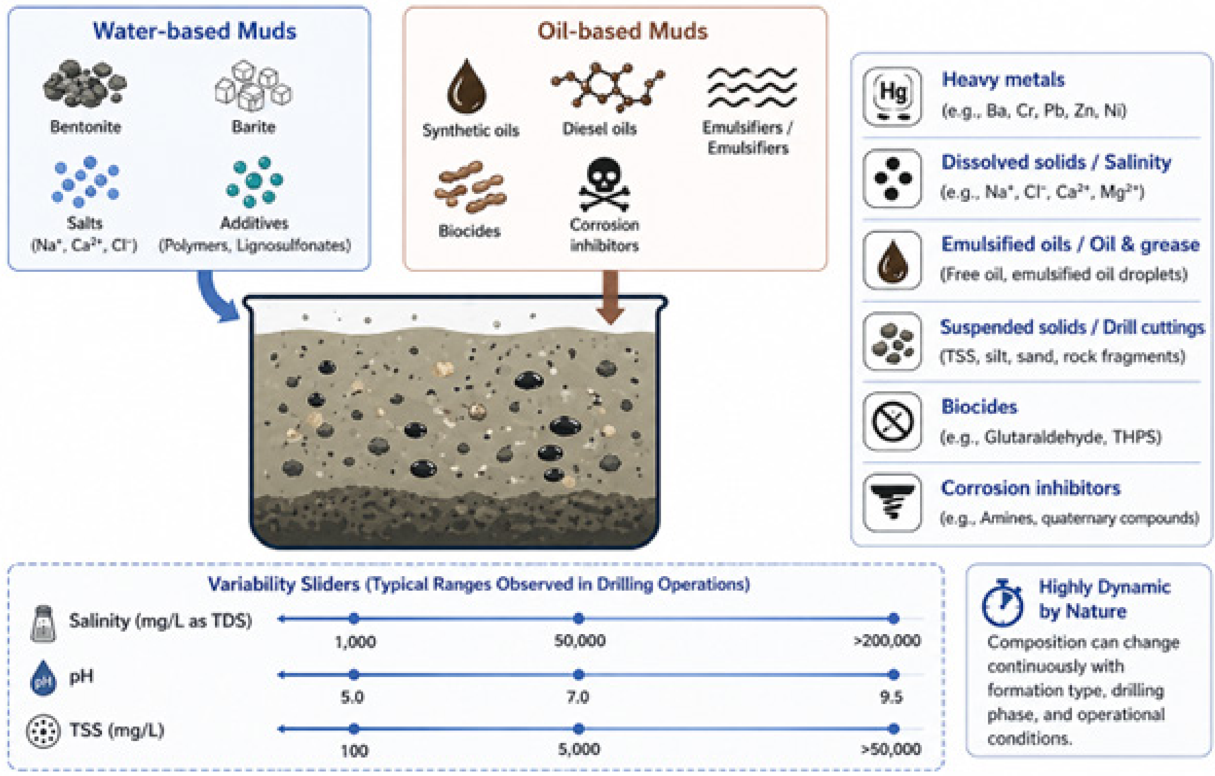

Figure 3. Key Characteristics and Variability of Drilling Wastewater

3.Conventional and Advanced Treatment Technologies

Although a wide range of physical, chemical, biological, and hybrid treatment technologies has been proposed for drilling wastewater management, their performance and applicability vary significantly depending on wastewater composition, operational scale, and site constraints (Dhadumia, Paul et al. 2025). Therefore, a purely descriptive comparison is insufficient for engineering decision-making. A critical evaluation considering treatment efficiency, energy demand, economic feasibility, and technology maturity is required to identify realistic and scalable solutions for industrial deployment (Yang, Sun et al. 2023).

Drilling wastewater treatment has traditionally relied on a combination of physical, chemical, and biological processes designed to reduce suspended solids, remove emulsified oil, neutralize hazardous constituents, and meet environmental discharge or reuse requirements (Ajao 2024). Physical treatment methods serve as the initial barrier against large quantities of solids and dispersed contaminants. Techniques such as sedimentation, screening, and centrifugation are commonly employed to separate drill cuttings and heavy particulates. Flotation systems, including dissolved air flotation, further enhance the removal of oil droplets and fine solids by promoting their aggregation and rise to the surface. Although these physical processes are simple, robust, and widely adopted in field operations, they often lack the capability to address dissolved contaminants or the chemically stabilized emulsions formed in oil-based and synthetic drilling systems. As a result, physical methods alone rarely achieve the stringent quality necessary for reinjection, reuse, or environmentally compliant discharge (Liu, Li et al. 2024).

Chemical treatment technologies represent another critical component of drilling wastewater management, particularly due to their ability to destabilize emulsions, precipitate dissolved metals, and oxidize recalcitrant organic pollutants. Coagulation-flocculation processes use metal salts or polymers to aggregate colloids and reduce turbidity, forming sludge that can be removed by sedimentation or filtration. Chemical oxidation, using agents such as ozone, hydrogen peroxide, or persulfate, targets persistent hydrocarbons and additives that resist biological degradation. Meanwhile, advanced chemical approaches involving electrocoagulation and electro-oxidation offer improved performance with fewer chemical inputs, although they require higher energy consumption and more sophisticated infrastructure. Despite these advancements, chemical treatments often generate substantial volumes of secondary waste, such as sludge or spent reagents, which necessitate careful handling and disposal. Moreover, the efficiency of chemical processes can be highly sensitive to variations in wastewater composition, pH, and salinity, making their optimization challenging in dynamic drilling environments (De Maman, da Luz et al. 2022).

Biological treatment methods, though less commonly applied to drilling wastewater, have gained attention as sustainable alternatives capable of degrading organic pollutants through microbial metabolism. Systems such as activated sludge reactors, fixed-film bioreactors, and constructed wetlands have shown potential for removing biodegradable hydrocarbons, nitrogenous compounds, and some drilling additives. Phytoremediation, using plants to uptake or transform contaminants, offers another environmentally friendly approach, particularly for land-based systems. However, the high salinity, presence of biocides, and complex organic mixtures characteristic of drilling wastewater often inhibit microbial activity and reduce treatment efficiency. Consequently, biological processes typically require significant pretreatment or dilution to become viable, limiting their applicability in many upstream operations (Jain, Majumder et al. 2020).

In recent years, hybrid and membrane-based technologies have emerged as promising solutions capable of achieving higher treatment efficiencies while recovering water for reuse. Membrane filtration processes such as microfiltration, ultrafiltration, nanofiltration, and reverse osmosis can effectively remove fine particulates, dissolved organics, and salts, depending on membrane pore size and configuration. Hybrid systems that integrate membranes with physical or chemical pretreatment, advanced oxidation, or biological processes can address a broader spectrum of contaminants and reduce fouling. Nonetheless, membrane technologies are frequently constrained by high capital and operational costs, energy requirements, and susceptibility to fouling by oil, suspended solids, and scaling constituents. Furthermore, managing concentrated reject streams remains a significant challenge, especially in offshore or remote drilling locations where disposal options are limited (Warsinger, Chakraborty et al. 2018).

Overall, the range of technologies available for drilling wastewater treatment reflects a balance between robustness, efficiency, cost, and operational feasibility. While conventional approaches continue to play a foundational role, advanced and hybrid systems offer enhanced performance but bring new challenges related to cost, energy use, and sludge management. As drilling operations expand into more demanding environments and regulatory expectations tighten, there is a growing need for treatment solutions that are both scalable and adaptable to highly variable wastewater compositions. This underscores the importance of intelligent optimization strategies, circular resource recovery, and uncertainty-aware design elements that increasingly define the future landscape of drilling wastewater management (Li, Tiraferri et al. 2025).

Despite their widespread use, conventional physical and chemical treatments often fail to achieve consistent effluent quality under highly variable drilling wastewater conditions. Advanced technologies such as membrane filtration and electrochemical processes offer superior contaminant removal but are frequently constrained by high energy consumption, fouling, and operational complexity (Yuan and He 2015). Moreover, many proposed treatment methods remain at laboratory or pilot scale, highlighting a gap between academic development and industrial implementation. These limitations underscore the need for adaptive, intelligence-assisted, and uncertainty-aware treatment frameworks capable of responding to fluctuating influent characteristics (Pereira, Sad et al. 2022).

From a technology readiness perspective, only a limited number of drilling wastewater treatment methods have reached full industrial maturity. Physical separation, chemical coagulation, and dissolved air flotation systems generally exhibit high TRL values (8-9), whereas biological treatment, advanced oxidation, and hybrid membrane systems often remain at pilot or demonstration stages (TRL 5-7). This disparity in maturity highlights the importance of integrating emerging technologies cautiously and in combination with proven treatment processes (Teodoriu and Bello 2021, Pouran Manjily, Alborzi et al. 2024).

Recent advancements in drilling wastewater treatment increasingly rely on the integration of advanced treatment technologies with machine learning and probabilistic modeling approaches. While physical, chemical, biological, and membrane-based processes provide the fundamental mechanisms for contaminant removal, their performance is often constrained by the highly variable composition and dynamic operating conditions of drilling wastewater (Bai, Li et al. 2026).

Machine learning (ML) techniques enable the modeling of complex, nonlinear relationships between process parameters and treatment performance, allowing for improved prediction accuracy, real-time monitoring, and adaptive optimization of treatment systems. In parallel, probabilistic approaches such as uncertainty quantification (UQ), Bayesian inference, and Monte Carlo simulation provide a systematic framework for evaluating variability, propagating uncertainties, and supporting risk-informed decision-making (Kalhormohammadi and Khoramipour 2025).

The integration of these data-driven and probabilistic methods with conventional and advanced treatment technologies enhances system robustness, improves operational efficiency, and enables more reliable performance under fluctuating conditions. This combined approach facilitates the transition from static, design-based treatment strategies to dynamic, intelligent, and adaptive systems capable of meeting increasingly stringent environmental and regulatory requirements.

(Table 3) summarizes key treatment methods based on target contaminants, performance, energy demand, cost, and technology readiness level (TRL), highlighting their advantages and limitations for industrial-scale applications.

The comparison highlights the trade-offs between treatment efficiency, energy consumption, and operational complexity, emphasizing the need for integrated and adaptive treatment strategies.

Table 4. Comparative Evaluation of Pressure Enhancement Techniques

Treatment Category	Technology	Primary Target Contaminants	Typical Removal Performance	Energy Demand (kWh/m³)	CAPEX / OPEX*	TRL	Sludge / By-products	Key Industrial-Scale Limitations
Physical	Sedimentation / Screening	Coarse solids, cuttings	Low-Moderate	< 0.1	Low / Low	9	High solids residue	Ineffective for fine particles and dissolved pollutants
Physical	Centrifugation	Fine solids, oil droplets	Moderate	0.2-0.5	Medium / Medium	8-9	Concentrated solids	High maintenance, limited oil removal
Physical	Dissolved Air Flotation (DAF)	Oil, grease, fine solids	Moderate-High	0.3-0.6	Medium/ Medium	8-9	Oily sludge	Sensitive to influent variability and chemical dosing
Chemical	Coagulation-Flocculation	Colloids, emulsified oil, metals	Moderate-High	0.1-0.5	Low / Medium	8-9	High chemical sludge	Sludge handling and disposal costs
Chemical	Chemical Oxidation (AOPs)	Recalcitrant organics	High	1-4	High / High	6-7	Minimal solids	High energy and reagent consumption
Chemical	Electrocoagulation / Electro-oxidation	Oil, metals, COD	High	2-6	Medium / High	6-7	Metal hydroxide sludge	Electrode fouling and energy demand
Biological	Activated Sludge / Biofilm	Biodegradable organics	Moderate	0.3-1.2	Medium / Medium	5-7	Biological sludge	Salinity and biocide inhibition
Biological	Constructed Wetlands	Organics, nutrients	Low-Moderate	< 0.2	Low / Low	5-6	Biomass	Large footprint, slow kinetics
Membrane-Based	MF / UF	TSS, oil droplets	High	0.5-2	High / Medium	7-8	Concentrated reject	Fouling by oil and solids
Membrane-Based	NF / RO	Dissolved salts, organics	Very High	2-6	High / High	7-9	High-salinity brine	Fouling, scaling, concentrate disposal
Hybrid Systems	Physical + Membrane / AOP	Broad contaminant spectrum	Very High	2-8	High / High	6-7	Mixed waste streams	System complexity and control requirements

*CAPEX/OPEX: qualitative order-of-magnitude comparison (Low / Medium / High).

4. Circular Economy Integration

The integration of circular economy principles into drilling wastewater management represents a significant shift from traditional linear disposal practices toward strategies that conserve resources, reduce environmental burdens, and enhance operational resilience (Digitemie, Onyeke et al. 2025). In drilling operations, water reuse and re-injection have emerged as central components of circularity, particularly in regions where water scarcity and regulatory constraints make fresh water procurement increasingly challenging. Treated drilling wastewater can be reused directly in mud formulation, rig wash operations, or hydraulic systems after appropriate conditioning, thereby reducing the demand for freshwater intake. Additionally, re-injection into deep geological formations offers an alternative disposal pathway that minimizes surface contamination risks. However, re-injection requires that wastewater quality meet strict chemical and particulate thresholds to prevent reservoir damage and clogging, which in turn underscores the importance of advanced treatment methods and real-time monitoring systems capable of ensuring consistent water quality under variable operational conditions (Jamshidi, Saen et al. 2025).

A fundamental opportunity for circularity lies in the recovery and valorization of valuable components embedded within drilling wastewater. Materials such as bentonite, barite, and high-value hydrocarbons are routinely lost during drilling operations despite their significant economic and functional importance in mud formulation. Advanced separation techniques, including hydrocycloning, membrane filtration, and tailored chemical treatments, allow for the recovery of these materials with sufficient purity for reuse. For example, barite a weighting agent with considerable market value can be separated from finer solids and recycled into new mud systems, reducing material consumption and operational costs. Similarly, hydrocarbons recovered from oil-based mud waste streams can be refined and reintegrated into drilling or other industrial processes. The ability to recover and repurpose these constituents not only minimizes waste generation but also transforms drilling wastewater from a liability into a secondary resource stream, reinforcing the economic viability of circular practices (Lihu and Jiahe 2025).

Zero liquid discharge (ZLD) presents an ambitious but powerful approach within the circular economy framework, particularly for offshore environments or isolated drilling sites where wastewater disposal options are limited. ZLD systems aim to eliminate liquid effluents entirely by combining evaporation, crystallization, and advanced concentration technologies to separate water and recover solid residues. While ZLD offers near-total environmental protection and maximum resource recovery, it is often associated with high energy consumption, significant capital costs, and the need for robust pre-treatment to prevent scaling and fouling within thermal systems. Nonetheless, emerging innovations such as forward osmosis, membrane distillation, and hybrid thermal-membrane processes are reducing the barriers to ZLD implementation, suggesting that future drilling operations may increasingly adopt closed-loop systems with minimal to zero discharge footprints (Panagopoulos and Michailidis 2025).

Life cycle assessment (LCA) provides critical insights into the broader sustainability implications of circular drilling wastewater strategies. Through LCA, trade-offs among energy consumption, emissions, material recovery, and environmental impacts can be systematically evaluated across the entire treatment and reuse chain. For instance, while advanced membrane systems may offer high contaminant removal efficiency and support water reuse, they may also incur higher energy footprints compared to simpler, conventional options (Thompson and Dvorak 2024). Conversely, resource recovery processes may offset environmental burdens by reducing the need for virgin material extraction, thereby yielding net-positive sustainability outcomes. LCA studies also highlight the importance of operational context, as the environmental benefits of circular strategies may vary depending on site-specific factors such as energy mix, waste composition, regulatory requirements, and logistical constraints. Ultimately, integrating LCA into decision-making enables operators to design drilling wastewater management systems that maximize circularity while minimizing unintended environmental trade-offs.

Overall, circular economy integration represents a transformative pathway for drilling wastewater management, shifting the industry toward more sustainable, resource-efficient, and low-impact operations. By closing material and water loops, recovering valuable resources, adopting ZLD technologies, and employing

LCA-driven optimization, drilling activities can move closer to achieving fully intelligent and circular wastewater systems that support long-term environmental and economic sustainability (Kundu, Dutta et al. 2022).

(Table 4) illustrates key circular economy strategies for drilling wastewater, emphasizing water reuse, resource recovery, and zero liquid discharge pathways alongside their associated benefits and challenges.

Table 4. Circular Economy Pathways in Drilling Wastewater Management (Albusaimi, Al Dabbous et al. 2024, Gaurina-Međimurec, Simon et al. 2024, Digitemie, Onyeke et al. 2025)

Circular Strategy	Recovered Resource	Technology Used	Benefit	Main Challenge
Water reuse	Treated water	Membranes, AOP	Reduced freshwater use	Quality consistency
Material recovery	Barite, bentonite	Flotation, separation	Cost savings	Separation efficiency
Hydrocarbon recovery	Base oil	Skimming, extraction	Resource valorization	Emulsion stability
ZLD	Salts, solids	Evaporation, crystallization	Zero discharge	High energy demand

(Figure 4) illustrates the circular economy-oriented framework for drilling wastewater management, highlighting how treatment technologies enable closed-loop water reuse, material recovery, and zero-liquid discharge pathways.

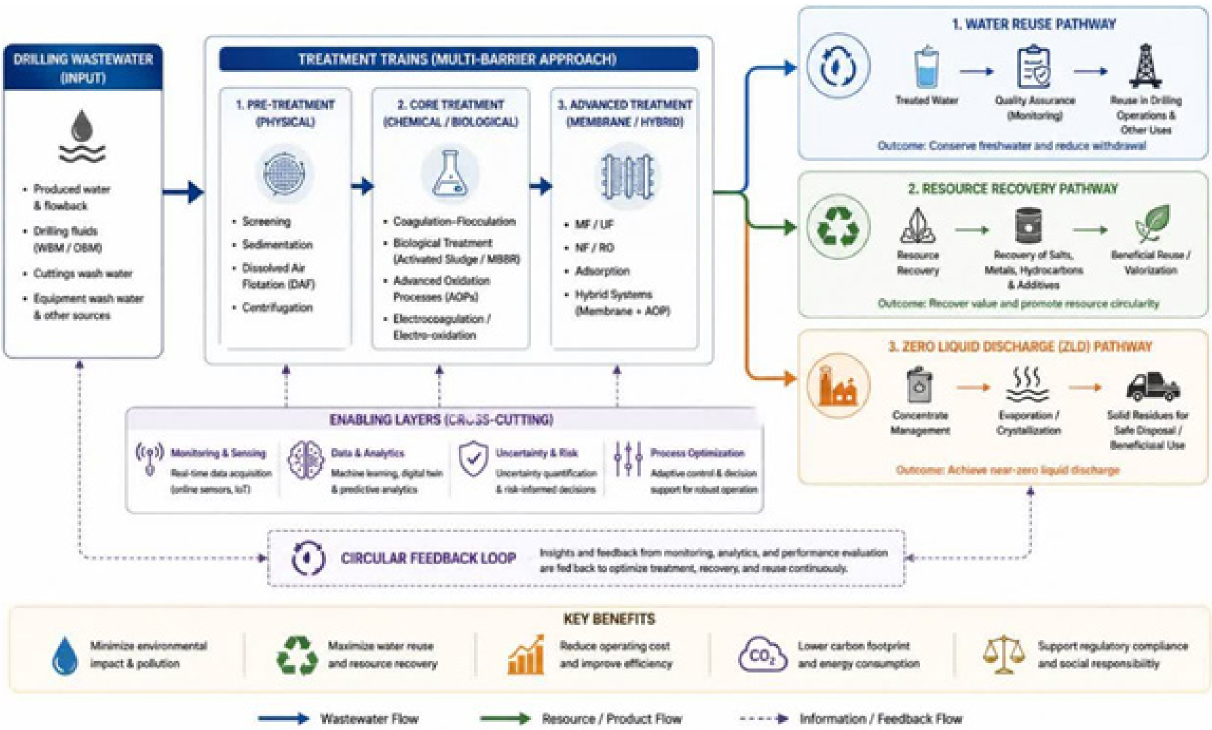

Figure 4. Circular Economy Pathways in Drilling Wastewater Management

(Figure 5). Circular economy pathways for drilling wastewater management, illustrating how treatment processes enable closed-loop water reuse and recovery of valuable materials such as barite, bentonite, and hydrocarbons, with optional life cycle assessment to evaluate energy use and emission reduction benefits.

Figure 5. Circular Economy Framework for Drilling Wastewater Management with Life Cycle Considerations

5. Data-Driven Intelligence in Treatment Optimization

The application of data-driven intelligence in drilling wastewater treatment has emerged as a powerful enabler for enhancing system performance, reducing operational uncertainties, and supporting adaptive decision-making (Zhou, Shi et al. 2023). Machine learning (ML), in particular, provides the ability to model highly nonlinear relationships between wastewater characteristics, treatment processes, and performance outcomes relationships that are often too complex to capture using traditional mechanistic models. One of the most prominent ML applications in this domain is performance prediction, where algorithms learn from historical datasets to estimate contaminant removal efficiency, optimal chemical dosing, membrane fouling rates, or energy consumption. Predictive models allow operators to forecast treatment outcomes under varying wastewater compositions, enabling proactive adjustments and reducing reliance on trial-and-error approaches. These capabilities are especially valuable in drilling contexts, where wastewater properties shift rapidly due to changes in geological formations, mud formulations, and drilling phases (Matheri, Mohamed et al. 2022, Kalhormohammadi and Khoramipour 2025).

Machine learning also plays a critical role in real-time monitoring, where sensor-derived data streams such as turbidity, conductivity, pressure, flow rates, and oil-in-water concentrations are processed to provide continuous insight into treatment system health. ML-driven monitoring frameworks can filter noise, detect subtle patterns, and identify emergent deviations that may not be apparent through manual observation. Coupled with edge computing and Internet of Things (IoT) technologies, these systems enable near-instantaneous diagnostic capabilities, improving operational visibility even in remote or offshore drilling environments. Beyond monitoring, ML offers significant advancements in process control and anomaly detection, wherein algorithms autonomously adjust process parameters such as coagulant dosage, pH, aeration rate, or membrane backwash cycles to maintain optimal performance. Anomaly detection models often based on unsupervised learning or neural network autoencoders can identify abnormal behaviors indicative of equipment failure, fouling events, or chemical imbalances before they escalate into costly operational disruptions (Tawfik 2024).

A wide range of machine learning algorithms has been applied to drilling wastewater treatment optimization, each offering distinct advantages depending on the complexity of the dataset and the nature of the prediction or classification task (Cangialosi, Bruno et al. 2021). Artificial neural networks (ANNs) are widely used for modeling nonlinear and multi-dimensional process relationships, particularly when dealing with large datasets and complex interactions among treatment variables. Support vector machines (SVMs) excel in classification tasks and are effective when datasets are moderate in size but require robust separation of classes, such as distinguishing normal from abnormal operating states. Random forest models provide strong performance in both regression and classification tasks while offering interpretability through feature importance metrics that help identify influential process parameters. Other emerging approaches include gradient boosting machines, deep learning architectures, Gaussian process regression, and reinforcement learning, which further expand the analytical capabilities for process optimization, adaptive control, and policy development. The diversity of available algorithms enables tailored model selection based on specific treatment objectives and data characteristics.

Despite these advancements, the successful application of data-driven approaches depends heavily on data quality, availability, and representativeness. Drilling wastewater datasets often suffer from issues such as sparse measurements, inconsistent sampling protocols, missing values, and limited long-term monitoring, all of which restrict model robustness. Additionally, operating conditions in drilling environments such as intermittent sampling, harsh field conditions, and rapid shifts in wastewater composition can introduce noise and variability that undermine model accuracy. A major challenge lies in transferability, as models trained on data from one region, mud formulation, or treatment system may not generalize effectively to others. Differences in contaminant profiles, sensor configurations, and process dynamics can cause significant performance degradation when models are applied outside their training domain. To address these challenges, techniques such as data augmentation, domain adaptation, hybrid mechanistic-ML modeling, and uncertainty quantification are increasingly employed to enhance model reliability and interpretability across diverse operational settings (Alsabaa, Gamal et al. 2022).

Overall, data-driven intelligence provides a transformative foundation for optimizing drilling wastewater treatment by enabling predictive accuracy, real-time responsiveness, and autonomous process control. As sensor technologies improve and data availability expands, machine learning will play an increasingly central role in designing intelligent, adaptive treatment systems capable of navigating the variability and complexity inherent in drilling wastewater management (Fisher, Wang et al. 2025).

While machine learning provides powerful tools for prediction, optimization, and process control, its effectiveness in drilling wastewater treatment is strongly influenced by data uncertainty and operational variability (Aparna, Swarnalatha et al. 2024). Sensor noise, missing data, and temporal changes in wastewater composition can significantly affect model accuracy and generalizability. Therefore, uncertainty quantification is not a complementary addition but a critical component for reliable ML deployment (Zidaoui 2024). Integrating uncertainty-aware ML models enables probabilistic prediction of treatment performance rather than deterministic estimates, thereby supporting risk-informed operational decisions (Asad and Everhart 2025). These probabilistic outputs can directly inform circular economy strategies by identifying operating conditions under which water reuse, material recovery, or zero-liquid-discharge pathways remain both technically feasible and economically viable (Pandey and Technology 2025).

(Table 5) categorizes major machine learning applications in drilling wastewater treatment, linking algorithm types to specific operational tasks, data inputs, and performance improvements.

Table 5. Machine Learning Applications in Drilling Wastewater Treatment (Olukoga, Feng et al. 2021, Sundui, Ramirez Calderon et al. 2021, Kalhormohammadi and Khoramipour 2025)

ML Task	Algorithm	Input Data	Output	Key Benefit
Performance prediction	ANN	Water quality, flow	Removal efficiency	Nonlinear modeling
Classification	SVM	Sensor data	Normal/fault	Robust detection
Optimization	Random Forest	Process parameters	Optimal settings	Interpretability
Anomaly detection	Autoencoders	Time-series data	Fault signals	Early warning

(Figure 6) presents a data-driven intelligent treatment framework in which machine learning, real-time sensor data, and uncertainty quantification support adaptive optimization of drilling wastewater treatment, resource recovery, and water reuse.

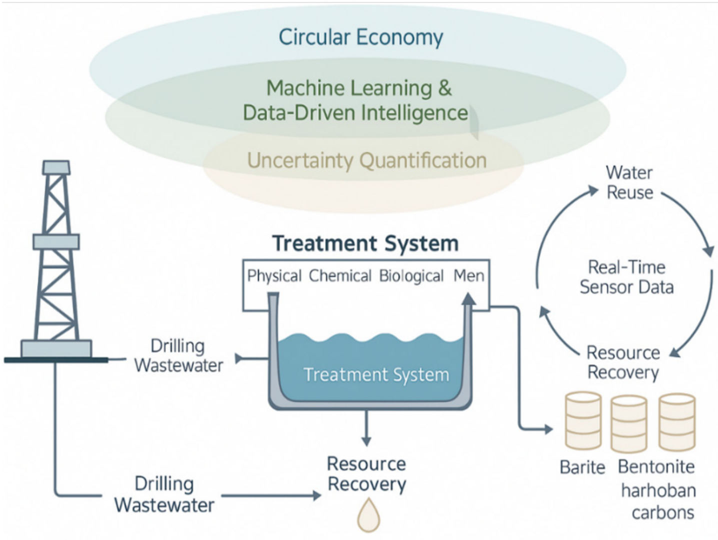

Figure 6. Data-Driven Intelligent Framework for Drilling Wastewater Treatment Optimization

6. Uncertainty Quantification in Treatment Modeling

In drilling wastewater treatment systems, uncertainty arises not only from wastewater composition and operational conditions but also from data-driven models used for performance prediction and optimization. When machine learning models are applied without explicit consideration of uncertainty, decision-making may be biased toward overly optimistic outcomes (Al-Dahidi, Alrbai et al. 2024). Consequently, uncertainty quantification provides the analytical foundation for integrating machine learning into robust and resilient treatment frameworks, ensuring that circular economy objectives such as reuse and resource recovery are achieved under realistic and variable field conditions (Nagpal, Siddique et al. 2024).

Uncertainty quantification has become an essential component of drilling wastewater treatment modeling due to the inherently variable and unpredictable nature of wastewater characteristics, operational conditions, and treatment system responses. One of the primary sources of uncertainty arises from input variability, as drilling wastewater composition changes continuously with geological formations, mud formulations, chemical additives, and drilling stages (Khalili, Ahmadi et al. 2023). These fluctuations affect contaminant loads, salinity, pH, and the presence of oils and emulsifiers, making it difficult to predict treatment performance using fixed-input models. Additionally, model structure uncertainty stems from the simplifying assumptions typically used in mechanistic or empirical models, such as linear relationships, steady-state conditions, or uniform reaction kinetics. These assumptions rarely hold under real field conditions, especially for processes involving membrane fouling, chemical dosing dynamics, or biological degradation. Parameter estimation uncertainty further complicates the task, as key parameters such as reaction rate constants, adsorption coefficients, or fouling indices are often derived from limited or inconsistent datasets, leading to calibration errors that propagate throughout the model (Shokir, Sallam et al. 2024).

To address these challenges, researchers increasingly contrast deterministic and probabilistic modeling approaches. Deterministic models rely on fixed input values and produce single-point predictions, which can be useful for initial design or operational planning but fail to capture the range of possible outcomes under variable conditions. In contrast, probabilistic models incorporate statistical distributions to represent uncertainty in inputs, parameters, or model structure, generating a spectrum of possible results rather than a single prediction. This probabilistic perspective is more aligned with the fluctuating reality of drilling operations, where treatment performance, contaminant removal efficiency, or system reliability may vary significantly from day to day. By quantifying the likelihood of different scenarios, probabilistic approaches provide a more comprehensive understanding of system behavior and are better suited for guiding operational strategies in environments where variability is the norm (Nooraiepour, Masoudi et al. 2021).

Bayesian methods and Monte Carlo simulations play pivotal roles in modern uncertainty quantification frameworks for drilling wastewater treatment. Bayesian approaches allow model parameters to be updated continually as new data become available, offering a dynamic mechanism for refining predictions and reducing uncertainty over time (Rasouli, Karimpour-Fard et al. 2025). This is particularly beneficial in treatment systems equipped with real-time monitoring sensors, where continuous data streams can enhance model accuracy and adaptability. Bayesian inference also provides posterior distributions for parameters and predictions, enabling transparent uncertainty characterization and improved decision-making under incomplete information. Monte Carlo simulations, on the other hand, use repeated random sampling to propagate input uncertainties through the treatment model, producing probability distributions of outputs such as effluent quality, sludge volume, or energy consumption. These simulations are especially useful for evaluating operational risks, identifying worst-case scenarios, and estimating the likelihood of regulatory compliance under varying wastewater conditions.

The integration of uncertainty quantification into treatment modeling offers significant implications for risk-informed decision-making. By explicitly accounting for variability and unknowns, operators can develop treatment strategies that are resilient rather than merely optimized for average conditions. Probabilistic insights enable more informed choices regarding treatment technology selection, operational setpoints, contingency planning, and investment decisions. For example, uncertainty-aware models can reveal whether a membrane system is likely to experience fouling beyond acceptable limits, whether chemical dosing needs to be adjusted to accommodate fluctuations in solid content, or whether reuse water will consistently meet reinjection quality standards. Furthermore, incorporating uncertainty into decision frameworks facilitates compliance with environmental regulations by highlighting conditions under which treatment systems may fail to meet discharge criteria, allowing operators to implement safeguards before violations occur. Ultimately, uncertainty quantification enhances both environmental protection and operational reliability by supporting decisions that are robust, adaptive, and grounded in the probabilistic realities of drilling wastewater management (Iseri, Iseri et al. 2025).

The integration of machine learning, uncertainty quantification, and circular economy principles enables a shift from reactive wastewater treatment toward intelligent and risk-informed circular systems. Machine learning models provide real-time predictions and optimization strategies, uncertainty quantification characterizes the reliability of these predictions, and circular economy frameworks translate model outputs into resource-efficient decisions (Lin, Wei et al. 2023). For example, uncertainty-aware ML models can identify optimal recovery pathways for barite or hydrocarbons while quantifying the probability of meeting reuse or discharge standards. This integrated approach supports resilient system design, minimizes environmental risk, and enhances economic performance under highly variable drilling conditions (Sircar, Yadav et al. 2021).

To translate emerging treatment technologies, machine learning, and circular economy principles into practical applications, a clear and structured implementation roadmap is required. (Figure 1) presents an integrated framework for intelligent and circular drilling wastewater management, illustrating how physical treatment processes, data-driven intelligence, and uncertainty-aware decision-making can be systematically combined within a closed-loop system (Rotan, Goettel et al. 2024).

The proposed roadmap begins with comprehensive wastewater characterization using online and offline sensors to capture temporal variability in key parameters such as oil content, salinity, and suspended solids (Nautiyal, Mishra et al. 2025). These data streams serve as inputs to machine learning models trained to predict treatment performance, optimize operating conditions, and detect anomalies in real time. Uncertainty quantification methods, including probabilistic modeling and Bayesian inference, are then applied to characterize the reliability of model predictions and propagate data and model uncertainties through the decision-making process (Gaurina-Međimurec, Simon et al. 2024).

Based on uncertainty-aware model outputs, risk-informed decisions are made regarding treatment pathways, water reuse, material recovery, or zero-liquid-discharge implementation. Circular economy objectives are operationalized by selecting recovery strategies that maximize resource value while maintaining regulatory compliance and system robustness under variable conditions (Daramola, Apeh et al. 2023). Feedback from treatment performance and recovery outcomes is continuously used to update models and reduce uncertainty, enabling adaptive and self-optimizing operation over time (Kandpal, Jaswal et al. 2024).

The proposed roadmap can be summarized in the following steps:

1. Real-time wastewater characterization and data acquisition;
2. ML-based performance prediction and operational optimization;
3. Uncertainty quantification and risk assessment;
4. Circular economy-based decision-making (reuse, recovery, ZLD);
5. Feedback-driven model updating and adaptive control.

(Table 6) identifies the principal sources of uncertainty in drilling wastewater treatment systems and summarizes the probabilistic methods used to quantify their impact on modeling accuracy and decision-making.

Table 6. Sources and Methods of Uncertainty Quantification (Iskandarani, Wang et al. 2016, Reichert and Technology 2020, Belia, Neumann et al. 2021)

Uncertainty Source	Description	Modeling Method	Decision Impact
Input variability	Changing wastewater composition	Monte Carlo	Risk estimation
Parameter uncertainty	Poorly calibrated constants	Bayesian inference	Robust design
Model uncertainty	Simplified assumptions	Ensemble models	Confidence bounds
Operational uncertainty	Sensor noise, failures	Probabilistic ML	Reliability

(Figure 7) illustrates an uncertainty-aware decision-making framework in which probabilistic modeling, real-time sensor data, and machine learning jointly inform adaptive control of drilling wastewater treatment and resource recovery.

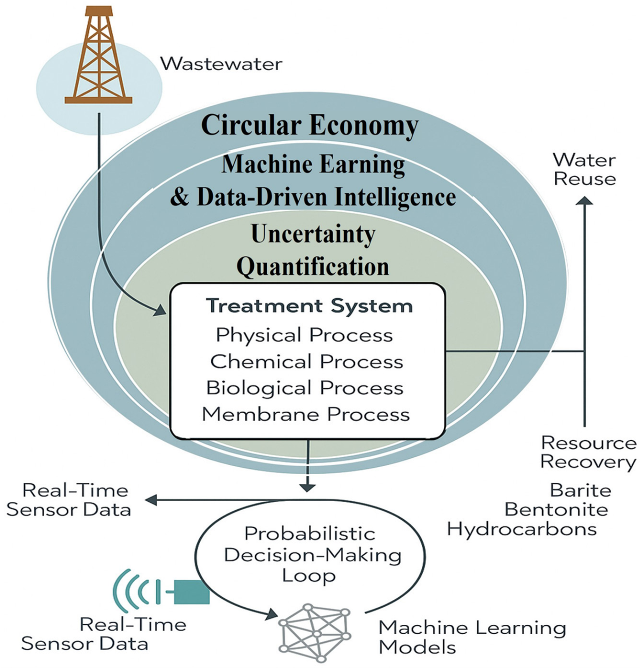

Figure 7. Integrated Machine Learning-Driven Wastewater Treatment System with Uncertainty-Aware Decision-Making

(Figure 8). Conceptual framework for uncertainty quantification and probabilistic decision-making in drilling wastewater treatment, illustrating how multiple sources of uncertainty are propagated through Bayesian inference and Monte Carlo simulation to support risk-informed and adaptive operational control.

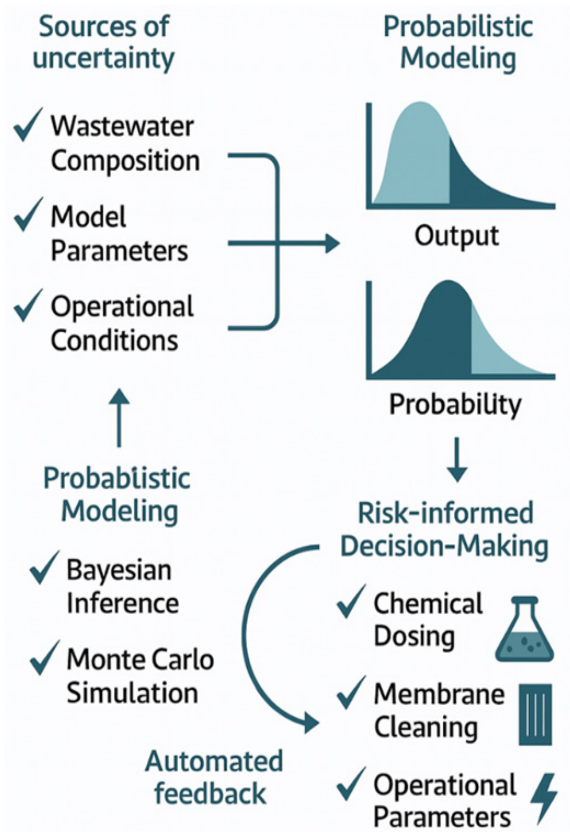

Figure 8. Conceptual Framework For Uncertainty Quantification In Drilling Wastewater Treatment Systems

7. Application of Artificial Intelligence in Operational Systems

The application of artificial intelligence (AI) in drilling wastewater treatment has evolved from theoretical modeling to practical, operation-level implementation. AI technologies enable real-time monitoring, adaptive control, predictive maintenance, and decision support, allowing treatment systems to respond dynamically to highly variable wastewater characteristics. This section highlights the key operational roles of AI in modern wastewater treatment systems (Sajib, Jaman et al. 2025).

7.1. Real-Time Process Monitoring

Real-time monitoring is a fundamental component of AI-enabled wastewater treatment systems. By integrating advanced sensors with machine learning algorithms, key parameters such as total suspended solids (TSS), oil content, salinity, and pH can be continuously tracked. AI models analyze incoming data streams to detect variations in wastewater composition and identify trends that may not be visible through conventional monitoring methods. This capability enables early detection of process deviations and supports more responsive and accurate system control (Shaaban 2025).

7.2. AI-Based Process Control

AI-driven control systems allow for the automatic adjustment of operational parameters in response to changing conditions. Machine learning models can optimize variables such as chemical dosing, pH levels, and flow rates in real time, improving treatment efficiency and reducing chemical and energy consumption. These systems operate within closed-loop control frameworks, where continuous feedback from sensors is used to update control decisions dynamically. This approach enhances system stability and ensures consistent performance under fluctuating operational conditions (Anyanwu, Agunwamba et al. 2026).

7.3. Predictive Maintenance

Predictive maintenance is another key application of AI in wastewater treatment operations. By analyzing historical and real-time data, AI models can detect early signs of equipment degradation, including membrane fouling, pump inefficiencies, and mechanical wear. This enables operators to perform maintenance activities proactively rather than reactively, reducing downtime, extending equipment lifespan, and lowering operational costs. Predictive maintenance also improves system reliability and minimizes the risk of unexpected failures.

7.4. Anomaly Detection

AI-based anomaly detection systems are designed to identify abnormal behavior in treatment processes. These systems can detect deviations from normal operating conditions, such as sudden changes in contaminant levels, unexpected process fluctuations, or sensor malfunctions. Early identification of anomalies allows for rapid corrective action, preventing system failures and ensuring compliance with environmental regulations. This capability is particularly important in complex and variable drilling environments (Anyanwu, Agunwamba et al. 2026).

7.5. Decision Support Systems

AI-driven decision support systems provide operators with actionable insights to guide wastewater management strategies. These systems can evaluate multiple scenarios and recommend optimal decisions, such as whether to reuse treated water, discharge it, or recover valuable resources. By integrating operational data, predictive models, and uncertainty analysis, decision support tools enhance operational efficiency and support more informed and sustainable decision-making processes (Jin, Liu et al. 2025).

7.6. Industrial Implementation Challenges

Despite the advantages of AI in operational systems, several challenges remain in large-scale implementation. Data availability and quality continue to be significant limitations, as many operations lack sufficient high-resolution datasets for effective model training. Sensor reliability and maintenance are also critical concerns, particularly in harsh drilling environments. In addition, integrating AI systems with existing infrastructure can be complex and may require significant investment and technical expertise. Addressing these challenges is essential for the successful adoption of AI-driven wastewater treatment systems in industrial settings (Jin, Liu et al. 2025).

(Table 7) summarizes representative pilot-scale applications of intelligent and circular drilling wastewater treatment systems, highlighting key technologies, performance outcomes, and operational conditions.

Table 7. Representative Pilot-Scale and Industrially Relevant Applications of Intelligent and Circular Drilling Wastewater Treatment (Ejairu, Aderamo Et Al. 2024, Aryanti, Nugroho Et Al. 2025, Ferri And Bolelli 2025)

Application Area	Scale	Approach	Demonstrated Benefit	Key Limitation
Solids & oil removal	Industrial	Centrifugation, DAF	Robust bulk removal	Limited dissolved removal
Chemical dosing control	Pilot	ML-based optimization	Reduced reagent use	Data availability
Drilling fluid monitoring	Field-like	ANN, RF models	Improved process control	Model transferability
Barite recovery	Industrial	Physical separation	Reduced material costs	Recovery efficiency
Water reuse	Pilot	Membrane systems	Lower freshwater demand	Fouling, energy use

8. Challenges and Limitations

Despite significant advancements in drilling wastewater treatment technologies and the growing integration of intelligent and circular approaches, several challenges and limitations continue to hinder large-scale implementation and operational efficiency. These limitations span data availability, technological performance, machine learning applicability, operational constraints, and economic and regulatory factors (Ghasemi, Akbari et al. 2025).

8.1. Data-Related Limitations

One of the primary challenges in developing intelligent wastewater treatment systems is the lack of standardized and high-quality datasets. Drilling wastewater characteristics vary significantly across locations and operations, leading to inconsistent sampling and data heterogeneity. In many cases, available datasets are limited in size, poorly structured, or lack temporal resolution, which restricts their usability for machine learning applications. These limitations directly affect model training, validation, and generalization, reducing the reliability of data-driven approaches (Liu, Dong et al. 2026).

8.2. Technological Limitations

Although advanced treatment technologies such as membrane filtration and advanced oxidation processes offer high removal efficiencies, they are often associated with operational challenges. Membrane fouling remains a critical issue, leading to reduced performance and increased maintenance requirements. Additionally, many advanced processes are energy-intensive, resulting in higher operational costs and environmental burdens. Sludge generation and management also present ongoing challenges, particularly in chemical and biological treatment systems, where disposal and handling can be complex and costly (Tian, Ma et al. 2026).

8.3. Machine Learning Limitations

While machine learning provides powerful tools for modeling and optimization, its application in drilling wastewater treatment is constrained by several factors. Model transferability remains a major issue, as models trained on one dataset may not perform well under different operational conditions. Data scarcity and variability further limit model robustness, while noise and uncertainty in measurements can affect prediction accuracy. These limitations highlight the need for more robust, interpretable, and adaptable machine learning frameworks (Tian, Ma et al. 2026).

8.4. Operational Challenges

Real-world implementation of advanced and intelligent treatment systems is often complicated by harsh operating environments typical of oil and gas operations. Extreme temperatures, high salinity, and variable flow conditions can affect both treatment processes and monitoring systems. Sensor reliability and maintenance pose additional challenges, particularly for real-time data acquisition. Furthermore, achieving fully integrated, real-time control systems requires significant infrastructure and technical expertise, which may not always be available (Zhou, Deng et al. 2025).

8.5. Economic and Policy Constraints

The adoption of advanced treatment technologies and intelligent systems is often limited by high capital and operational expenditures. Technologies such as membrane systems and zero liquid discharge (ZLD) require substantial investment, which may not be economically feasible in all cases. In addition, regulatory frameworks vary across regions and may lack clear guidelines for emerging technologies. Limited financial incentives and policy support further slow the transition toward circular and sustainable wastewater management practices (Zhou, Deng et al. 2025).

9. Future Directions

Future advancements in drilling wastewater treatment are expected to be driven by the convergence of intelligent systems, advanced sensing technologies, and circular economy strategies. These developments aim to transform conventional treatment approaches into adaptive, efficient, and sustainable systems capable of operating under highly variable and uncertain conditions (Dhadumia, Paul et al. 2026).

9.1. Intelligent and Autonomous Treatment Systems

The development of intelligent and autonomous treatment systems represents a key direction for future research and industrial implementation. Artificial intelligence (AI)-driven control strategies can enable real-time adjustment of operational parameters such as chemical dosing, flow rates, and membrane pressures. These systems have the potential to evolve into fully self-optimizing treatment plants that continuously learn from operational data, improving efficiency, reducing human intervention, and enhancing system reliability under dynamic conditions (Wang, Li et al. 2025).

9.2. Integration of Machine Learning, Uncertainty Quantification, and Digital Twins

The integration of machine learning (ML), uncertainty quantification (UQ), and digital twin technologies offers significant opportunities for advancing wastewater treatment systems. Digital twins virtual replicas of physical systems can simulate process behavior in real time, allowing for predictive analysis and scenario evaluation. When combined with ML and UQ, these systems enable real-time adaptive control, improved prediction accuracy, and risk-informed decision-making, supporting more robust and resilient treatment operations (Dhadumia, Paul et al. 2026).

9.3. Advanced Sensing and Data Infrastructure

Future systems will increasingly rely on advanced sensing technologies and data infrastructure to support continuous monitoring and control. The deployment of Internet of Things (IoT) devices and high-frequency sensors enables real-time data acquisition for key parameters such as salinity, oil content, and suspended solids. These technologies improve data availability and quality, which are essential for training machine learning models and enabling responsive, data-driven system management.

9.4. Expansion of Circular Economy Strategies

Circular economy principles will play an increasingly important role in the future of drilling wastewater management. Advancements in zero liquid discharge (ZLD) technologies will enhance water recovery efficiency and reduce environmental discharge. In addition, improved resource recovery techniques such as the extraction of hydrocarbons, salts, and valuable minerals will contribute to economic value generation and waste minimization. These developments support the transition toward closed-loop systems that maximize resource utilization and sustainability (Wang, Li et al. 2025).

9.5. Policy and Industrial Implementation

The successful implementation of advanced and intelligent wastewater treatment systems will depend on supportive regulatory frameworks and industry adoption. Future efforts should focus on developing clear regulations for emerging technologies, establishing standardized operational guidelines, and providing economic incentives for sustainable practices. Collaboration between academia, industry, and policymakers will be essential to accelerate technology deployment and ensure that innovative solutions are effectively translated into large-scale industrial applications (Loss, Cavali et al. 2026).

(Table 8) outlines the major technical, data-related, and policy-driven gaps in current drilling wastewater management practices and highlights future research directions toward intelligent and circular treatment systems.

Table 8. Research Gaps and Future Opportunities (Matheri, Mohamed et al. 2022, Adedayo-Ojo, Shad et al. 2025, Waware, Nagalli et al. 2025)

Gap	Current Limitation	Future Direction
Data availability	Fragmented datasets	Standardized databases
ML deployment	Limited real-time use	Sensor-ML integration
Circular adoption	High capital cost	Policy incentives
System intelligence	Manual control	Autonomous treatment systems

Figure 9 presents a future-oriented vision of AI-driven and zero-liquid-discharge-enabled wastewater management integrated across the oil and gas value chain, highlighting long-term sustainability and investment pathways.

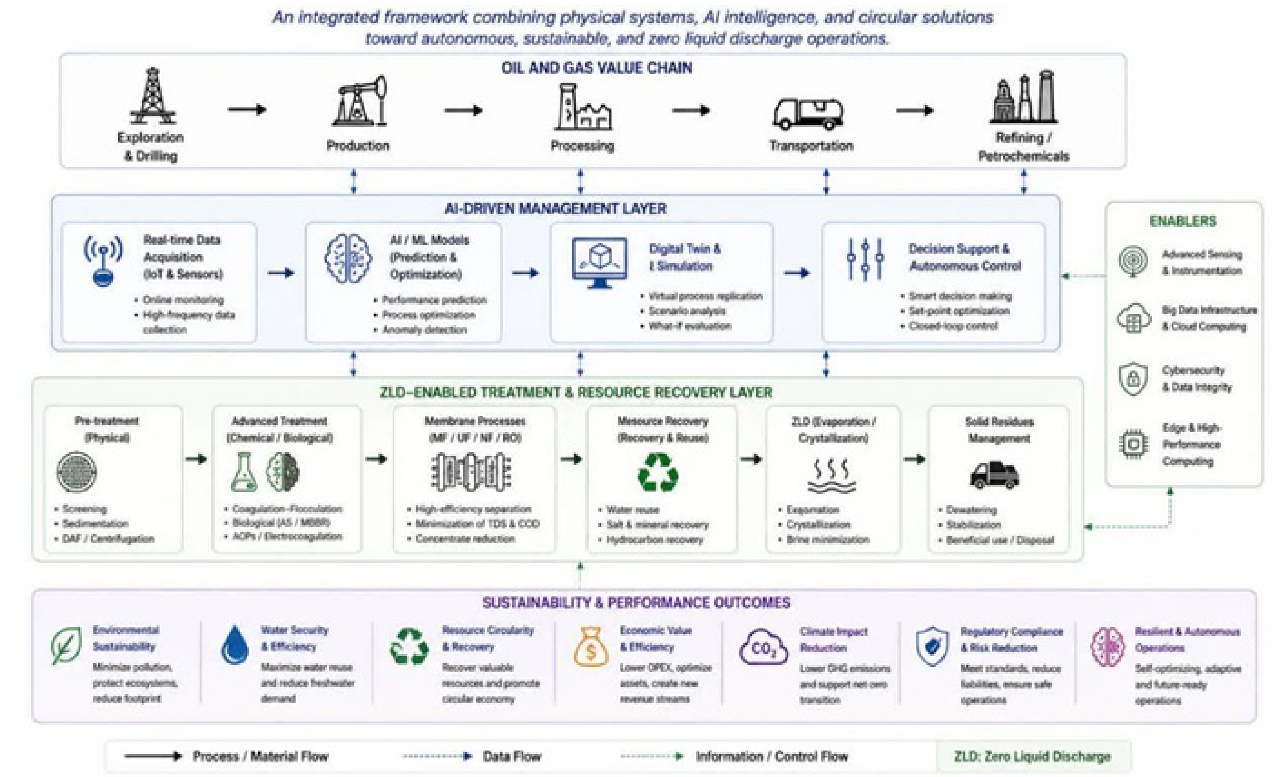

Figure 9. Future Integrated AI-Driven and Zero Liquid Discharge (ZLD) Wastewater Management Framework

Figure 10. Visionary framework for real-time optimized, autonomous, and intelligent drilling wastewater management, illustrating how machine learning, digital twins, and adaptive control enable circular economy-based resource recovery and near-zero discharge operation under human-in-the-loop oversight.

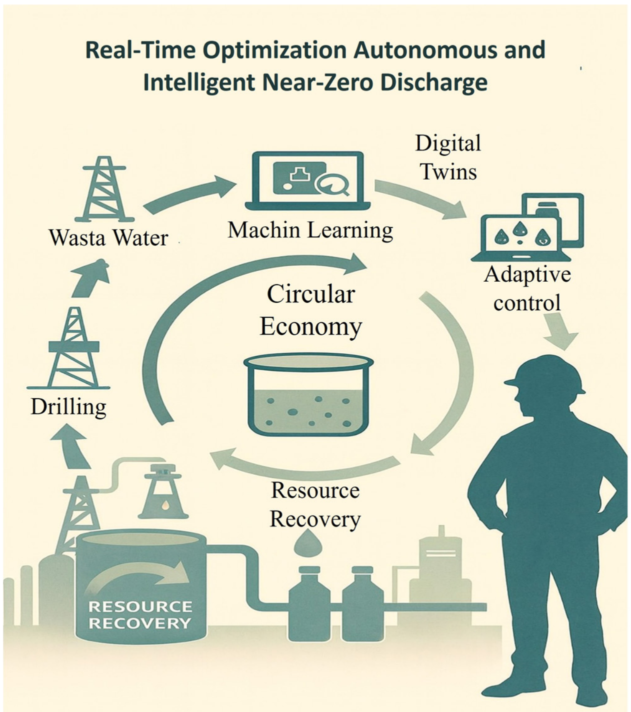

Figure 10. Vision Of Autonomous and Intelligent Drilling Wastewater Treatment Systems

10. Conclusion

This review has presented a comprehensive and integrated analysis of drilling wastewater treatment by bridging conventional and advanced treatment technologies with emerging approaches in machine learning, uncertainty quantification, and circular economy principles. The findings demonstrate that while physical, chemical, biological, and membrane-based processes remain the foundation of contaminant removal, their effectiveness is often constrained by the highly variable and dynamic nature of drilling wastewater systems.

The integration of data-driven intelligence, particularly machine learning, enables improved prediction, monitoring, and adaptive optimization of treatment processes under fluctuating operational conditions. In parallel, uncertainty quantification provides a robust framework for addressing variability and supporting risk-informed decision-making. Together, these approaches enhance system reliability, operational efficiency, and resilience, moving beyond traditional static treatment strategies toward dynamic and adaptive system design.

From a sustainability perspective, the adoption of circular economy strategies such as water reuse, resource recovery, and zero liquid discharge (ZLD) offers significant potential to reduce environmental impacts while improving resource efficiency and economic performance. These strategies support the transition from linear waste management practices to closed-loop systems that valorize wastewater streams and minimize environmental footprint.

Despite these advancements, several challenges remain, including limited data availability, difficulties in model generalization, high operational costs of advanced technologies, and integration barriers in real-world industrial environments. Addressing these limitations will require the development of standardized datasets, improved sensing and monitoring infrastructure, and scalable frameworks that integrate artificial intelligence into operational systems.

Future developments are expected to focus on autonomous treatment systems, digital twin technologies, and fully integrated, AI-driven platforms capable of real-time optimization and decision-making. Such advancements will play a critical role in achieving sustainable and resilient wastewater management in the oil and gas industry.

Overall, this study highlights the importance of interdisciplinary integration in advancing drilling wastewater treatment. By combining engineering processes with data science and sustainability principles, the proposed framework provides a pathway toward intelligent, adaptive, and circular wastewater management systems capable of meeting future environmental and industrial challenges.

Nomenclature

AI	Artificial Intelligence
ANN	Artificial Neural Network
AOP	Advanced Oxidation Process
CE	Circular Economy
DAF	Dissolved Air Flotation
DT	Digital Twin
IoT	Internet of Things
LCA	Life Cycle Assessment
ML	Machine Learning
MLD	Minimal Liquid Discharge
NF	Nanofiltration
O&G	Oil and Gas
RO	Reverse Osmosis
SVM	Support Vector Machine
TDS	Total Dissolved Solids
TSS	Total Suspended Solids
UQ	Uncertainty Quantification
WBM	Water-Based Mud
OBM	Oil-Based Mud
ZLD	Zero Liquid Dischargr

References

Adedayo-Ojo, A. A., M. K. Shad, W. C. J. C. E. Poon and Sustainability (2025). "Circular Economy in the Oil and Gas Industry: A Data-Driven Bibliometric Analysis." 1-63.

Adverse, A. T. N.-Z. "INTEGRATED SUSTAINABLE URBAN WATER, ENERGY, AND SOLIDS MANAGEMENT."

Ahmed, A., A. Alsaihati, S. J. A. J. f. S. Elkatatny and Engineering (2021). "An overview of the common water-based formulations used for drilling onshore gas wells in the Middle East." 46(7): 6867-6877.

Ajao, A. (2024). "Conventional and advanced treatment technologies for microplastics in water treatment facilities."

Al-Dahidi, S., M. Alrbai, L. Al-Ghussain, A. Alahmer and H. S. J. B. T. Hayajneh (2024). "Data-driven analysis and prediction of wastewater treatment plant performance: Insights and forecasting for sustainable operations." 391: 129937.

Albusaimi, F. A., M. S. Al Dabbous, R. Al Yateem and F. P. Pretorius (2024). Circular Economy Practices Through Water Management. SPE International Conference and Exhibition on Health, Safety, Environment, and Sustainability?, SPE.

Alessi, D. S., A. Zolfaghari, S. Kletke, J. Gehman, D. M. Allen and G. G. J. C. W. R. J. R. c. d. r. h. Goss (2017). "Comparative analysis of hydraulic fracturing wastewater practices in unconventional shale development: Water sourcing, treatment and disposal practices." 42(2): 105-121.

Alsabaa, A., H. Gamal, S. Elkatatny and Y. J. A. o. Abdelraouf (2022). "Machine learning model for monitoring rheological properties of synthetic oil-based mud." 7(18): 15603-15614.

Anyanwu, C., J. C. Agunwamba and M. J. A. o. A. I. i. R. o. E. C. Tiza (2026). "Application of conventional methods and artificial intelligence tools for wastewater treatment: Recent advancements and future prospects." 109-149.

Aparna, K., R. J. P. S. Swarnalatha and E. Protection (2024). "Optimizing wastewater treatment plant operational efficiency through integrating machine learning predictive models and advanced control strategies." 188: 995-1008.

Aryanti, P. T. P., F. A. Nugroho, C. Ahmadi, R. Ismail, A. J. M. o. P. W. Kadier, I. Oil Field Discharges: Diagnosis and Treatment (2025). "Water Recycling at Oil Field Industry Plants." 351-402.

Asad, G. and J. Everhart (2025). "Uncertainty-Aware Predictive Maintenance: Leveraging Adaptive Machine Learning for Mechanical Components."

Bai, Y., Z. Li, J. Jiang, J. Liu, H. Wang, Q. Liu, G. Gang, Z. Kong and Y. J. E. R. Wang (2026). "Optimizing wastewater treatment through combined deep learning and deep reinforcement learning: Recent advances and future prospects." 123795.

Ball, A. S., R. J. Stewart, K. J. W. M. Schliephake and Research (2012). "A review of the current options for the treatment and safe disposal of drill cuttings." 30(5): 457-473.

Barcelona, M. J., J. P. Gibb and R. A. Miller (1983). A guide to the selection of materials for monitoring well construction and ground-water sampling, Illinois State Water Survey.

Basu, S., A. R. Shaw and M. Venkatesh (2025). Water Management in Petroleum Industries, Springer Nature.

Belia, E., M. B. Neumann, L. Benedetti, B. Johnson, S. Murthy and P. Vanrolleghem (2021). Uncertainty in Wastewater Treatment Design and Operation, IWA Publishing.

Cangialosi, F., E. Bruno and G. J. S. De Santis (2021). "Application of machine learning for fenceline monitoring of odor classes and concentrations at a wastewater treatment plant." 21(14): 4716.

Chang, Y.-R., Y.-J. Lee and D.-J. J. J. o. t. T. I. o. C. E. Lee (2019). "Membrane fouling during water or wastewater treatments: Current research updated." 94: 88-96.

Daramola, O. M., C. E. Apeh, J. O. Basiru, E.

C. Onukwulu, P. O. J. J. o. C. E. Paul and S. L. Forthcoming (2023). "Optimizing reverse logistics for circular economy: Strategies for efficient material recovery and resource circularity."

De Maman, R., V. C. da Luz, L. Behling, A. Dervanoski, C. Dalla Rosa, G. D. L. J. E. S. Pasquali and P. Research (2022). "Electrocoagulation applied for textile wastewater oxidation using iron slag as electrodes." 29(21): 31713-31722.

Dhadumia, B., B. J. W. M. Paul and Research(2025). "A review of advanced sustainable waste management approaches of the oil and gas industry:Integrating green hybrid technologies for a cleaner future." 0734242X251385854.

Dhadumia, B., B. J. W. M. Paul and Research (2026). "A review of advanced sustainable waste management approaches of the oil and gas industry: Integrating green hybrid technologies for a cleaner future." 44(3): 237-251.

Digitemie, W. N., F. O. Onyeke, M. A. Adewoyin, I. N. J. I. J. o. M. R. Dienagha and G. Evaluation (2025). "Implementing circular economy principles in oil and gas: addressing waste management and resource reuse for sustainable operations." 6(1): 99-104.

Ejairu, U., A. T. Aderamo, H. C. Olisakwe, A. E. Esiri, U. M. Adanma, N. O. J. C. r. Solomon, r. i. Engineering and Technology (2024). "Eco-friendly wastewater treatment technologies (concept): Conceptualizing advanced, sustainable wastewater treatment designs for industrial and municipal applications." 2(1): 083-104.

Fernandes, J., P. J. Ramísio and H. J. E. Puga (2024). "A comprehensive review on various phases of wastewater technologies: Trends and future perspectives." 5(4): 2633-2661.

Ferri, E. N. and L. J. A. S. Bolelli (2025). "Wastewater remediation treatments aimed at water reuse: recent outcomes from pilot-and full-scale tests." 15(5): 2448.

Fisher, O. J., Y. Wang and A. J. W. R. Ahmed (2025). "Making waves: Transforming biofilm-based wastewater treatment using machine learning-driven real-time monitoring." 124491.

Gangwar, A., S. Rawat, A. Rautela, I. Yadav, A. Singh, S. J. E. Kumar, Development and Sustainability (2025). "Current advances in produced water treatment technologies: a perspective of techno-economic analysis and life cycle assessment." 27(7): 15077-15111.

Garg, M. C., S. Kumari and S. Agarwal(2024). The integration of artificial intelligence in advanced wastewater treatment systems. The AI Cleanse: Transforming Wastewater Treatment Through Artificial Intelligence: Harnessing Data-Driven Solutions, Springer: 1-27.

Gaurina-Međimurec, N., K. Simon, K. N. Mavar, B. Pašić, P. Mijić, I. Medved, V. Brkić, L. Hrnčević and K. Žbulj (2024). The circular economy in the oil and gas industry: a solution for the sustainability of drilling and production processes. Circular Economy on Energy and Natural Resources Industries: New Processes and Applications to Reduce, Reuse and Recycle Materials and Decrease Greenhouse Gases Emissions, Springer: 115-150.

Ghasemi, K., A. Akbari, S. Jahani and Y. J. T. C. J. o. C. E. Kazemzadeh (2025). "A critical review of life cycle assessment and environmental impact of the well drilling process." 103(6): 2499-2526.

Hossain, M. E., A. Al-Majed, A. R. Adebayo, A. S. Apaleke, S. M. J. E. E. Rahman and M. Journal (2017). "A CRITICAL REVIEW OF DRILLING WASTE MANAGEMENT TOWARDS SUSTAINABLE SOLUTIONS." 16(7).

Iseri, F., H. Iseri, H. Shah, E. Iakovou, E. N. J. C. Pistikopoulos and C. Engineering (2025). "Planning strategies in the energy sector: Integrating bayesian neural networks and uncertainty quantification in scenario analysis & optimization." 198: 109097.

Iskandarani, M., S. Wang, A. Srinivasan, W. Carlisle Thacker, J. Winokur and O. M. J. J. o. G. R. O. Knio (2016). "An overview of uncertainty quantification techniques with application to oceanic and oil-spill simulations." 121(4): 2789-2808.

Jain, M., A. Majumder, P. S. Ghosal and A. K. J. J. o. E. M. Gupta (2020). "A review on treatment of petroleum refinery and petrochemical plant wastewater: a special emphasis on constructed wetlands." 272: 111057.

Jamshidi, E., S. Saen, J. Golshaghagh, P. Kianoush, A. Adib and A. J. S. R. Mohammadi (2025). "Challenges of drilling Iran's deepest surface hole in the saddle section of Changuleh oilfield with complex structure and pressure regimes." 15(1): 25302.

Jin, J., M. Liu, B. Chen, X. Wu, L. Yao, Y. Wang, X. Xiong, L. Wei, J. Li and Q. J. S. Tan (2025). "Artificial Intelligence in Chemical Dosing for Wastewater Purification and Treatment: Current Trends and Future Perspectives." 12(9): 237.

Jin, X., L. Zhang, M. Liu, S. Hu, Z. Yao, J. Liang, R. Wang, L. Xu, X. Shi and X. J. C. Bai (2022). "Characteristics of dissolved ozone flotation for the enhanced treatment of bio-treated drilling wastewater from a gas field." 298: 134290.

Kalhormohammadi, M. and S. J. S. R. Khoramipour. (2025) "Predictive modeling of coagulant dosing in drilling wastewater treatment using artificial neural networks." 15(1): 30003.

Kandpal, V., A. Jaswal, E. D. Santibanez Gonzalez and N. Agarwal (2024). Circular economy principles: shifting towards sustainable prosperity. Sustainable energy transition: Circular economy and sustainable financing for environmental, social and governance (ESG) practices, Springer: 125-165.

Khalili, Y., M. J. J. o. C. Ahmadi and P. Engineering (2023). "Reservoir modeling & simulation: Advancements, challenges, and future perspectives." 57(2): 343-364.

Kundu, D., D. Dutta, P. Samanta, S. Dey, K. C. Sherpa, S. Kumar and B. K. J. S. o. t. T. E. Dubey (2022). "Valorization of wastewater: A paradigm shift towards circular bioeconomy and sustainability." 848: 157709.

Lawan, M. S., R. Kumar, J. Rashid and M. A. E.-F. J. W. Barakat (2023). "Recent advancements in the treatment of petroleum refinery wastewater." 15(20): 3676.

Lebedev, A. and A. J. R. Cherepovitsyn (2024). "Waste management during the production drilling stage in the oil and gas sector: a feasibility study." 13(2): 26.

Li, C., A. Tiraferri, P. Tang, J. Ma and B. J. W. R. Liu (2025). "Current status, potential assessment, and future directions of biological treatments of unconventional oil and gas wastewater." 123217.

Lihu, L. and S. J. P. O. Jiahe (2025). "A novel strategy for resource utilization of oily drilling waste fluids in northern Shaanxi: Stepwise flotation of bentonite and barite using SDS and interfacial reaction mechanisms." 20(8): e0331415.

Lin, K., S. J. J. o. g. e. Wei and l.-c. development (2023). "Advancing the industrial circular economy: the integrative role of machine learning in resource optimization." 2(3): 122-136.

Liu, F., Y. Li, X. Wang and Z. J. M. Xia (2024). "Preparation and properties of reversible emulsion drilling fluid stabilized by modified nanocrystalline cellulose." 29(6): 1269.

Liu, H., S. Dong, J. Yang, S. Liao, S. J. J. o. H. Liu, Toxic, and R. Waste (2026). "Treatment and Disposal Technologies for Oil-Based Drilling Cuttings: An Overview and Prospects." 30(1): 03125004.

Loss, L., M. Cavali, A. Freitas, S. Kubeneck, G. Leme, A. Calvo, S. Soares, A. J. I. J. o. E. S. de Castilhos Junior and Technology (2026). "Environmental aspects of drill cuttings from oil operations: characterization, risk assessment, valorization, and treatment innovations." 23(4): 307.

Matheri, A. N., B. Mohamed, F. Ntuli, E. Nabadda, J. C. J. P. Ngila and P. a. b. c. Chemistry of the Earth (2022). "Sustainable circularity and intelligent data-driven operations and control of the wastewater treatment plant." 126: 103152.

Nagpal, M., M. A. Siddique, K. Sharma, N. Sharma, A. J. W. S. Mittal and Technology (2024). "Optimizing wastewater treatment through artificial intelligence: recent advances and future prospects." 90(3): 731-757.

Nautiyal, A., A. K. J. E. Mishra, Development and Sustainability (2025). "Machine learning approach for intelligent prediction of petroleum upstream stuck pipe challenge in oil and gas industry." 27(10).

Nooraiepour, M., M. Masoudi and H. J. S. R. Hellevang (2021). "Probabilistic nucleation governs time, amount, and location of mineral precipitation and geometry evolution in the porous medium." 11(1): 16397.

Olukoga, T., Y. J. S. D. Feng and Completion (2021). "Practical machine-learning applications in well-drilling operations." 36(04): 849-867.

Panagopoulos, A. and P. J. M. Michailidis (2025). "Membrane technologies for sustainable wastewater treatment: Advances, challenges, and applications in zero liquid discharge (zld) and minimal liquid discharge (mld) systems." 15(2): 64.

Pandey, A. K. J. E. S. W. R. and Technology (2025). "Sustainable water management through integrated technologies and circular resource recovery." 11(8): 1822-1846.

Pereira, L. B., C. M. Sad, E. V. Castro, P. R. Filgueiras and V. J. F. Lacerda Jr (2022). "Environmental impacts related to drilling fluid waste and treatment methods: A critical review." 310: 122301.

Pouran Manjily, H., M. Alborzi, T. Behrouz, S. M. J. J. o. S. Seyed-Hosseini and T. P. Management (2024). "Intelligent oil field technology maturity level assessment: using the technology readiness level criteria." 15(6): 1223-1246.

Rasouli, M. A., M. Karimpour-Fard, S. L. J. J. o. t. A. Machado and W. M. Association (2025). "An assessment of the uncertainties of methane generation in landfills." 75(6): 464-482.

Reichert, P. J. W. S. and Technology (2020). "Towards a comprehensive uncertainty assessment in environmental research and decision support." 81(8): 1588-1596.

Rotan, K., Q. Goettel, K. Smith, A. Gonzalez, U. Onyemaobi and M. Yurukcu (2024). "AI/ML Technology for Water Treatment in Oil and Gas Industry: A Review Paper."

Sajib, M., A. Jaman, M. A. Ullah, M. A. B. H. Susan and M. S. Miran (2025). AI Technologies for Treating Petroleum Wastewater. Management of Petroleum Wastewater and Oil Field Discharges: Diagnosis, Impacts and Treatment, Springer: 81-118.

Sangamnere, R., T. Misra, H. Bherwani, A. Kapley and R. J. S. W. R. M. Kumar (2023). "A critical review of conventional and emerging wastewater treatment technologies." 9(2): 58.

Scheidt, C., L. Li and J. Caers (2018). Quantifying uncertainty in subsurface systems, John Wiley & Sons.

Shaaban, Y. A. (2025). Wastewater Treatment: Using AI and Response Surface Methodology to Predict and Optimize. Management of Petroleum Wastewater and Oil Field Discharges: Diagnosis, Impacts and Treatment, Springer: 27-45.

Shokir, E. M., S. Sallam and M. M. J. A. o. Abdelhafiz (2024). "Comprehensive Wellbore Stability Modeling by Integrating Poroelastic, Thermal, and Chemical Effects with Advanced Numerical Techniques." 9(52): 51536-51553.

Sircar, A., K. Yadav, K. Rayavarapu, N. Bist and H. J. P. R. Oza (2021). "Application of machine learning and artificial intelligence in oil and gas industry." 6(4): 379-391.

Smol, M., C. Adam, M. J. J. o. M. C. Preisner and W. Management (2020). "Circular economy model framework in the European water and wastewater sector." 22(3): 682-697.

Sundui, B., O. A. Ramirez Calderon, O. M. Abdeldayem, J. Lázaro-Gil, E. R. Rene, U. J. C. T. Sambuu and E. Policy (2021). "Applications of machine learning algorithms for biological wastewater treatment: updates and perspectives." 23(1): 127-143.

Tawfik, M. J. P. o. (2024). "Optimized intrusion detection in IoT and fog computing using ensemble learning and advanced feature selection." 19(8): e0304082.

Teodoriu, C. and O. J. E. Bello (2021). "An outlook of drilling technologies and innovations: Present status and future trends." 14(15): 4499.

Thacker, J. B., D. D. Carlton Jr, Z. L. Hildenbrand, A. F. Kadjo and K. A. J. W. Schug (2015). "Chemical analysis of wastewater from unconventional drilling operations." 7(4): 1568-1579.

Thompson, M. and B. J. W. E. R. Dvorak (2024). "Wastewater reuse benefits for municipal complete retention lagoons: Life cycle assessment and dynamic modeling." 96(8): e11098.

Tian, D., W. Ma, L. Du, H. Chen, Y. Zhou, J. Tan, P. Zhang, Y. Sun, B. Xiao, Y. J. W. Qu, Air, and S. Pollution (2026). "Challenges and Opportunities in Tunnel Wastewater Treatment: Engineering Perspectives for Sustainable Management." 237(6): 387.

Tsolakis, N., T. S. Harrington, J. S. J. P. P. Srai and Control (2023). "Digital supply network design: a Circular Economy 4.0 decision-making system for real-world challenges." 34(10): 941-966.

Wang, Z., S. Li, Z. Xu, S. A. Aryana and J. J. C. Cai (2025). "Advances and challenges in foam stability: Applications, mechanisms, and future directions." 15(3): 58-73.

Warsinger, D. M., S. Chakraborty, E. W. Tow, M. H. Plumlee, C. Bellona, S. Loutatidou, L. Karimi, A. M. Mikelonis, A. Achilli and A. J. P. i. p. s. Ghassemi (2018). "A review of polymeric membranes and processes for potable water reuse." 81: 209-237.

Waware, S. Y., N. K. Nagalli, S. Sugumaran, P. D. Patil, R. Biradar, A. A. Kadam, K. B. Ghunake, S. S. Kore, G. Murali, A. S. J. N.-J. o. S. Kurhade and T. Research (2025). "AI-Driven Innovations in the Exploration, Extraction, and Processing of Minerals, Metals, and Petroleum: A Review." 7(4): 209-227.

Wei, X., S. Zhang, Y. Han and F. A. J. W. E. R. Wolfe (2019). "Treatment of petrochemical wastewater and produced water from oil and gas." 91(10): 1025-1033.

Yang, H., H. Diao, Y. Zhang and S. J. J. o. e. m. Xia (2022). "Treatment and novel resource-utilization methods for shale gas oil based drill cuttings-A review." 317: 115462.

Yang, J., J. Sun, R. Wang, Y. J. E. s. Qu and p. research (2023). "Treatment of drilling fluid waste during oil and gas drilling: A review." 30(8): 19662-19682.

Yuan, H. and Z. J. B. t. He (2015). "Integrating membrane filtration into bioelectrochemical systems as next generation energy-efficient wastewater treatment technologies for water reclamation: A review." 195: 202-209.

Zhang, T. J. W. (2025). Sustainable wastewater treatment and the circular economy, MDPI. 17: 335.

Zhang, W., Q. Li, S. Dong, H. Liu, K. Dong, X. Wu, M. Sui and F. J. J. o. W. P. E. Zhang (2024). "Synthesis of mixed-base active material from drilling fluid solid waste and biomass for oil wastewater adsorption and its mechanism." 66: 106076.

Zhang, Y., P. Xu, M. Xu, L. Pu and X. J. A. o. Wang (2022). "Properties of bentonite slurry drilling fluid in shallow formations of deepwater wells and the optimization of its wellbore strengthening ability while drilling." 7(44): 39860-39874.

Zhou, J., T. Shi, Q. Qian, C. He and J. J. S. p. Ren (2023). "Protocol for the design and accelerated optimization of a waste-to-energy system using AI tools." 4(4): 102685.

Zhou, Y., C. Deng, X. Chen, Y. He, G. Fang, Z. Jin, Y. J. W. M. Liu and Research (2025). "Engineering design and application of large-scale oil-based drilling cuttings treatment project." 43(2): 282-292.

Zidaoui, I. (2024). Advanced data validation methods for wastewater sensors using Artificial Intelligence, Université de Strasbourg.

Zong, Z. and Y. J. J. o. t. k. e. Guan (2025). "AI-driven intelligent data analytics and predictive analysis in Industry 4.0: Transforming knowledge, innovation, and efficiency." 16(1): 864-903.

تصفیه هوشمند و چرخشی پساب حفاری: مروری بر یکپارچه‌سازی یادگیری ماشین، کمّی‌سازی عدم‌قطعیت و بازیابی منابع

- سید عطا الیاس سرخابی[۱]، محمدرضا اکبری[۲*]، یاسین خلیلی[۳]

۱. دانشجوی کارشناسی، دانشکده مهندسی نفت و زمین انرژی، دانشگاه صنعتی امیرکبیر، تهران، ایران

۲. استادیار، دانشکده مهندسی نفت و زمین انرژی، دانشگاه صنعتی امیرکبیر، تهران، ایران

۳. دانشجوی دکترا، دانشکده مهندسی نفت و زمین انرژی، دانشگاه صنعتی امیرکبیر، تهران، ایران

(ایمیل نویسنده مسئول: akbari.pe@aut.ac.ir)

چکیـــــده

پساب حفاری تولیدشده در عملیات نفت و گاز، به دلیل ترکیب بسیار متغیر، حجم زیاد، و حضور آلاینده‌های خطرناک آلی و معدنی، یکی از چالش‌های پیچیده زیست‌محیطی محسوب می‌شود. روش‌های متداول تصفیه، علی‌رغم کاربرد گسترده، اغلب در دستیابی به عملکرد پایدار تحت شرایط عملیاتی دینامیک و الزامات سخت‌گیرانه زیست‌محیطی با محدودیت مواجه هستند.

این مطالعه مروری، تحلیلی جامع و آینده‌نگر از مدیریت پساب حفاری ارائه می‌دهد که در آن فناوری‌های تصفیه با مفاهیم نوظهور اقتصاد چرخشی، هوشمندسازی مبتنی بر داده، و کمّی‌سازی عدم‌قطعیت به‌صورت یکپارچه مورد بررسی قرار گرفته‌اند. در این راستا، ویژگی‌ها و منابع تولید پساب حفاری بررسی شده تا ماهیت متغیر آن و چالش‌های مرتبط با تصفیه مشخص گردد. همچنین، فناوری‌های متداول، پیشرفته و هیبریدی تصفیه از نظر کارایی، محدودیت‌ها، و قابلیت کاربرد در بازیافت آب و بازیابی منابع به‌صورت انتقادی ارزیابی شده‌اند. راهبردهای اقتصاد چرخشی از جمله بازچرخانی آب، بازیابی مواد، و سیستم‌های تخلیه صفر مایع نیز از منظر پایداری مورد تحلیل قرار گرفته‌اند.

علاوه بر این، نقش یادگیری ماشین در پیش‌بینی عملکرد، بهینه‌سازی فرآیند، و پایش لحظه‌ای بررسی شده و در کنار آن، روش‌های کمّی‌سازی عدم‌قطعیت مانند مدل‌سازی احتمالاتی برای پشتیبانی از تصمیم‌گیری مبتنی بر ریسک مورد بحث قرار گرفته‌اند. از دیدگاه صنعتی، یکپارچه‌سازی مدل‌های هوشمند و چارچوب‌های مبتنی بر عدم‌قطعیت می‌تواند به توسعه سیستم‌های تصفیه‌ای قابل‌اعتمادتر، تطبیق‌پذیرتر و کاراتر منجر شود.

با وجود این پیشرفت‌ها، چالش‌هایی همچون محدودیت داده‌ها، انتقال‌پذیری مدل‌ها، پیچیدگی یکپارچه‌سازی سیستم‌ها، و ملاحظات اقتصادی همچنان پابرجاست. این مطالعه با ارائه یک چارچوب یکپارچه که مهندسی محیط‌زیست، علوم داده و اصول پایداری را به هم پیوند می‌دهد، مسیر توسعه سیستم‌های تصفیه پساب حفاری هوشمند، چرخشی و مقاوم را ترسیم می‌کند.

واژگان کلیدی: تصفیه پساب حفاری، یادگیری ماشین، کمّی‌سازی عدم‌قطعیت، اقتصاد چرخشی، بازیابی منابع، صنعت نفت و گاز

Journal of Gas Technology

VOLUME 10 • ISSUE 2 • WINTER 2025

EISSN: 2588-5596

Contents

www.jgt.irangi.org