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Data-Driven Performance Optimization of Produced Water Treatment Infrastructure, A Conceptual Modeling Approach

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ABSTRACT: Produced water (PW), the largest by-product of oil and gas operations, presents both environmental challenges and resource opportunities. Variability in chemical composition, flow rate, and contaminant load, coupled with the energy-intensive nature of conventional treatment, limits operational efficiency and the potential for resource recovery. This review presents a conceptual modeling framework for data-driven performance optimization of PW treatment infrastructure, integrating digital monitoring, artificial intelligence (AI), and predictive modeling to enhance operational resilience and resource utilization. The framework emphasizes real-time data acquisition through advanced sensor technologies, Internet of Things (IoT) connectivity, and edge or cloud-based data analytics. Machine learning algorithms are proposed for pattern recognition, anomaly detection, predictive maintenance, and dynamic process optimization, enabling adaptive control of chemical dosing, membrane operations, retention times, and bio-based treatment units. The approach also supports integrated resource recovery, including nutrient extraction (nitrogen and phosphorus), biomass harvesting and valorization for bioenergy or soil amendments, and salt and mineral recovery for industrial applications. Scenario modeling allows treatment systems to accommodate temporal and spatial variability in PW composition while maximizing water reuse and resource efficiency. Additionally, the framework incorporates energy considerations, including integration with renewable energy sources, and environmental risk mitigation through early warning systems and predictive alerts for system failure or contamination spikes. Pilot applications and case studies demonstrate the potential for improved treatment efficiency, reduced energy consumption, enhanced resource recovery, and operational resilience. By synthesizing digital monitoring, AI-based optimization, and modular treatment design within a unified conceptual model, this framework offers a pathway toward sustainable, circular water management in energy operations. Adoption of such data-driven approaches can transform PW from a waste liability into a strategic resource stream, supporting environmental compliance, economic efficiency, and operational sustainability.

KEYWORDS: Produced water, resource recovery, data-driven optimization, artificial intelligence, digital monitoring, hybrid treatment systems, circular water management, predictive modeling, off-grid operations, sustainability.

1.0 INTRODUCTION

Produced water (PW) is the largest by-product generated during oil and gas extraction, accounting for significant volumes relative to hydrocarbons produced. PW is a complex mixture of formation water, injected fluids, dissolved salts, hydrocarbons, heavy metals, nutrients, and naturally occurring radioactive materials (NORM). Its composition varies substantially between wells, fields, and production phases, reflecting geological heterogeneity, operational practices, and extraction techniques (Aniebonam et al., 2025; Taiwo et al., 2025). Globally, billions of barrels of PW are generated annually, posing significant environmental and operational challenges if not effectively managed. In addition to disposal concerns, such as potential groundwater contamination or surface discharge impacts, the high volume and variable composition of PW demand treatment infrastructure capable of meeting regulatory requirements while enabling resource recovery and potential reuse (Kuponiyi, 2025; Ofori et al., 2025).

Treatment infrastructure for PW faces multiple challenges. First, the inherent variability in PW composition including fluctuations in salinity, hydrocarbons, suspended solids, and nutrient loads complicates treatment design and operational control (Akpan, 2025; Adenuga et al., 2025). Second, many conventional physicochemical and biological treatment processes are energy-intensive, requiring substantial chemical dosing, pumping, and thermal input, which increases operational costs and carbon footprint. Third, operational inefficiencies arise from equipment fouling, scaling, inconsistent effluent quality, and the inability of conventional systems to dynamically respond to changing water characteristics (Olufemi, 2025; Olisa, 2025). Collectively, these challenges can reduce system performance, limit resource recovery potential, and increase environmental and economic risks.

Conventional monitoring and manual process control are limited in addressing these complexities. Most PW treatment systems rely on periodic sampling and laboratory analysis to guide operational decisions, resulting in delays and reactive management (Adeshina, 2025; Adeoye et al., 2025). Manual adjustments of chemical dosing, retention times, or flow rates are often based on experience rather than real-time data, leaving systems vulnerable to deviations in water quality or process inefficiencies. Such approaches are insufficient for optimizing hybrid treatment trains, integrating bio-based recovery processes, or supporting adaptive reuse strategies, particularly in remote or off-grid operations where operational oversight is constrained (Aniebonam, 2025; Rathilall and Akpan, 2025).

Data-driven approaches and conceptual modeling offer a solution to these limitations. By integrating digital sensors, Internet of Things (IoT) connectivity, and machine learning algorithms, treatment infrastructure can be monitored continuously, and process parameters can be dynamically optimized in real time (Oyeyemi et al., 2025; Adeshina and Poku, 2025). Conceptual models provide a framework for simulating system behavior under variable conditions, predicting performance outcomes, and supporting decision-making for chemical dosing, membrane operation, aeration, and bio-based nutrient or biomass recovery (Adeleke, 2025; Fowowe et al., 2025). These approaches facilitate adaptive control, enhance energy and resource efficiency, and enable the integration of circular water management principles.

The objective of this, is to develop a conceptual modeling framework for data-driven performance optimization of PW treatment infrastructure. The framework emphasizes real-time monitoring, predictive and prescriptive analytics, hybrid treatment system integration, and modular design for scalability and adaptability. The study aims to synthesize current knowledge on sensor technologies, AI-based control, and resource recovery strategies, providing a structured approach for enhancing treatment efficiency, operational resilience, and sustainable reuse of produced water. Ultimately, this framework seeks to transform PW management from a reactive, disposal-focused process into a proactive, resource-oriented, and environmentally sustainable operation.

2.0 METHODOLOGY

To develop a comprehensive conceptual framework for data-driven performance optimization of produced water (PW) treatment infrastructure, a systematic review methodology was employed. Peer-reviewed journal articles, conference proceedings, and technical reports were retrieved from scientific databases including Scopus, Web of Science, and Google Scholar, focusing on studies published between 2000 and 2025. Search terms combined key concepts such as “produced water,” “treatment optimization,” “data-driven monitoring,” “artificial intelligence,” “predictive modeling,” “hybrid treatment systems,” and “resource recovery.”

Inclusion criteria encompassed studies reporting experimental, pilot-scale, or modeling applications of PW treatment systems with measurable performance outcomes, as well as publications detailing digital monitoring, AI-based process optimization, or integrated resource recovery. Exclusion criteria filtered out studies lacking quantitative performance data, those not relevant to PW, or reports without application to energy operations. Duplicate records were removed, and remaining studies were screened through title and abstract review, followed by full-text assessment to ensure relevance to the objectives of the conceptual framework.

Data extraction captured key parameters including treatment technology types (physicochemical, bio-based, or hybrid), monitoring approaches, AI or digital control strategies, energy consumption, effluent quality metrics, and resource recovery outcomes (nutrients, biomass, salts). Temporal and spatial variability in PW composition, system adaptability, and integration with circular water management principles were also recorded.

The methodological approach followed a modified PRISMA flow, documenting the number of records identified, screened, assessed for eligibility, and included in the synthesis. This process enabled systematic collation and critical appraisal of literature on data-driven and AI-enabled PW treatment systems. Findings informed the development of a conceptual model that integrates real-time digital monitoring, machine learning-driven process optimization, modular treatment configurations, and adaptive control strategies for enhanced performance, energy efficiency, and resource recovery. The approach ensures the framework is grounded in evidence-based practices while addressing current technological, operational, and sustainability challenges in produced water management.

2.1 Conceptual Framework for Data-Driven PW Treatment Optimization

Data-driven performance optimization represents an emerging approach in produced water (PW) management, combining real-time monitoring, predictive analytics, and adaptive process control to improve treatment efficiency, reduce energy consumption, and enhance resource recovery (Essandoh et al., 2025; Adeoye et al., 2025). In the context of PW treatment infrastructure, data-driven optimization encompasses the continuous collection, analysis, and application of operational and water quality data to guide system operation dynamically, rather than relying solely on conventional periodic sampling or fixed operational protocols. This paradigm shift allows treatment systems to respond proactively to temporal and spatial variability in PW composition, fluctuations in flow rates, and operational disturbances, ultimately supporting sustainable and resilient water management.

The scope of data-driven PW treatment optimization extends across multiple treatment scales and technology types. Hybrid treatment systems—integrating physicochemical processes such as membrane filtration, adsorption, and advanced oxidation with bio-based processes like biofilm reactors, algal consortia, and constructed wetlands—can benefit from continuous optimization. Data-driven approaches provide actionable insights for each unit operation, including chemical dosing, hydraulic retention time, aeration rates, and membrane flux. Additionally, digital monitoring enables the evaluation of system performance in real time, ensuring compliance with effluent quality standards for water reuse, industrial processes, or environmental discharge.

Central to the conceptual framework is the integration of monitoring, control, and predictive analytics. Advanced sensor networks continuously capture key water quality parameters, including salinity, total dissolved solids (TDS), chemical oxygen demand (COD), total suspended solids (TSS), hydrocarbons, nutrient concentrations, and pH. These sensors, connected via Internet of Things (IoT) platforms, transmit data to cloud-based or edge-computing systems for analysis. Machine learning algorithms then process the data to identify trends, detect anomalies, and predict potential operational issues such as membrane fouling, biofilm performance decline, or chemical overdosing (Odezuligbo and Qin, 2025; Oni, 2025). Predictive analytics enable proactive interventions, while prescriptive models recommend optimal operational adjustments to maximize treatment efficiency and minimize chemical and energy inputs.

Modeling plays a critical role in simulating PW treatment processes and operational scenarios within this framework. Conceptual and computational models can represent each treatment unit’s kinetics, mass transfer, and removal efficiency under varying influent conditions. Scenario modeling allows operators to evaluate how changes in PW composition, flow rates, or environmental conditions may impact overall system performance. These models also provide a platform for testing alternative treatment configurations, resource recovery strategies, and adaptive control policies before deployment in field systems. By simulating potential outcomes, modeling informs the design of resilient and scalable treatment architectures that maintain effluent quality and support beneficial reuse objectives.

System-level objectives of the framework are multifaceted. First, maximizing treatment efficiency ensures that suspended solids, hydrocarbons, nutrients, salts, and other contaminants are effectively removed or recovered, enabling reuse in industrial, agricultural, or enhanced oil recovery applications. Second, minimizing energy and chemical use addresses both operational cost and environmental impact, particularly in off-grid or remote energy operations where energy supply may be constrained (Aniebonam et al., 2025; Udechukwu et al., 2025). Third, ensuring effluent quality through continuous monitoring and predictive control safeguards environmental compliance, protects downstream ecosystems, and supports public and regulatory confidence in PW reuse strategies.

The conceptual framework also emphasizes modularity and adaptability. Modular treatment units allow incremental capacity expansion, while AI-driven process control enables dynamic adjustments in response to real-time changes in PW characteristics. Integration with resource recovery processes, such as nutrient extraction, biomass harvesting, and salt reclamation, aligns treatment with circular water management principles. Moreover, the framework supports integration with renewable energy systems, facilitating sustainable and resilient off-grid operation.

A conceptual framework for data-driven PW treatment optimization integrates real-time monitoring, predictive analytics, and adaptive control to improve treatment efficiency, resource recovery, and operational resilience. By combining modeling, hybrid treatment systems, and AI-enabled control, the framework provides a systematic approach to managing the complexity of PW treatment, minimizing energy consumption, ensuring effluent quality, and supporting circular water management. This approach transforms PW treatment infrastructure from a reactive, disposal-oriented operation into a proactive, sustainable, and resource-focused system, capable of meeting the evolving demands of the oil and gas sector.

2.2 Characterization of Produced Water for Modeling

Produced water (PW), the largest by-product of oil and gas operations, is a complex, heterogeneous fluid whose properties are critical for the design, optimization, and modeling of treatment systems. Accurate characterization of PW is essential for developing predictive models, optimizing treatment efficiency, and supporting resource recovery and beneficial reuse. The inherent variability in chemical composition, physical properties, and flow rate introduces significant challenges for modeling, system design, and operational control (Oyeyemi et al., 2025; Adeshina, 2025). Understanding the composition and variability of PW is therefore a foundational step in implementing data-driven and model-based optimization strategies.

PW exhibits a broad spectrum of chemical and physical characteristics influenced by geological formations, production techniques, reservoir conditions, and the type and volume of injected fluids. Salinity is one of the most critical parameters, often expressed as total dissolved solids (TDS), which can range from a few thousand to over 200,000 mg/L in high-salinity reservoirs. Elevated salinity levels affect osmotic pressure, membrane fouling potential, and the efficiency of physicochemical and biological treatment units. The ionic composition, including concentrations of sodium, calcium, magnesium, potassium, chloride, sulfate, and bicarbonate, influences scaling, corrosion, and chemical dosing requirements.

Hydrocarbons, present as dispersed oils or dissolved organic compounds, pose environmental risks and operational challenges such as emulsion formation and membrane fouling. Concentrations of total petroleum hydrocarbons (TPH) can vary widely, affecting pre-treatment and adsorption requirements. Heavy metals, including arsenic, lead, cadmium, and mercury, may occur naturally or be mobilized from reservoir rocks. Their presence necessitates additional removal steps to meet environmental discharge standards or reuse quality criteria. Naturally occurring radioactive materials (NORM) may also accumulate in PW, particularly in certain offshore reservoirs, and require careful monitoring for occupational safety and environmental protection.

Nutrients, particularly nitrogen and phosphorus, are present in varying concentrations depending on the injection fluids and reservoir microbial activity. Organic matter, including dissolved organic carbon (DOC) and volatile fatty acids, provides both a potential energy source for bio-based treatment and a challenge in controlling effluent quality (Adeoye et al., 2025; Oni and Iloeje, 2025). Collectively, these chemical and physical properties define the baseline conditions for predictive modeling, treatment selection, and resource recovery design.

PW characteristics exhibit significant temporal and spatial variability. Flow rates fluctuate with production cycles, reservoir depletion, water cut, and operational interventions, affecting hydraulic retention times and treatment capacity requirements. Similarly, contaminant concentrations—including salinity, hydrocarbons, nutrients, and metals—can vary over time, reflecting changes in reservoir pressure, formation water composition, or production techniques. Spatial variability is evident between different wells, fields, and reservoirs, with offshore PW often showing higher salinity and hydrocarbon content than onshore PW, and onshore fields demonstrating more variability in metals and nutrients due to heterogeneous geology.

This variability has profound implications for modeling and system design. Predictive models must account for dynamic influent conditions to accurately simulate treatment unit performance, contaminant removal efficiency, and resource recovery potential. Models that assume steady-state conditions or uniform PW composition risk underestimating fouling, scaling, or treatment inefficiencies, leading to operational failures or suboptimal resource recovery. Incorporating temporal and spatial variability into modeling enables scenario analysis, adaptive control, and the development of robust, resilient treatment systems capable of handling fluctuating water quality and flow rates.

Effective characterization informs the selection of treatment technologies, hybrid process configurations, and operational strategies. For instance, high TDS and scaling ions may necessitate pre-treatment with ion exchange, softening, or selective precipitation prior to membrane filtration. Hydrocarbon content determines the need for oil-water separation or adsorption units. Nutrient and organic matter profiles guide bio-based treatment design, including microbial consortia selection and retention time optimization (Jimoh and Omiyefa, 2025; Olufemi et al., 2025). Heavy metals and NORM concentrations influence regulatory compliance strategies and dictate monitoring frequency and analytical methods.

From a modeling perspective, detailed characterization enables the development of mechanistic, data-driven, or hybrid models that simulate unit operation performance under variable conditions. These models can predict effluent quality, energy consumption, fouling potential, and recovery efficiency, supporting real-time optimization and resource management. Moreover, understanding variability allows modular system design, ensuring scalability and adaptability for both onshore and offshore operations.

Comprehensive characterization of PW including chemical, physical, and nutrient properties, as well as temporal and spatial variability is critical for predictive modeling and optimization of treatment infrastructure. Accurate data on salinity, TDS, hydrocarbons, heavy metals, organics, and nutrients provides the foundation for selecting treatment processes, designing hybrid systems, and enabling AI-driven performance optimization. Accounting for variability ensures models are robust and treatment systems are resilient, scalable, and capable of supporting sustainable water reuse and resource recovery. Ultimately, detailed PW characterization underpins the transition from reactive disposal practices to proactive, data-driven, and circular water management strategies in oil and gas operations (Udechukwu et al., 2025; Essandoh et al., 2025).

2.3 Data Acquisition and Digital Monitoring

Effective performance optimization of produced water (PW) treatment infrastructure relies heavily on accurate, timely, and continuous data collection. Variability in PW composition, flow rates, and operational conditions presents significant challenges for conventional monitoring techniques, which are often periodic, labor-intensive, and prone to delays. Digital monitoring and advanced data acquisition frameworks provide the foundation for real-time performance assessment, predictive control, and resource recovery optimization (Ike et al., 2025; Ajidahun and Abdulrazaq, 2025). By integrating sensor technologies, Internet of Things (IoT) connectivity, and intelligent data processing strategies, PW treatment systems can transition from reactive management to proactive, adaptive operation.

High-resolution sensors form the backbone of digital monitoring in PW treatment systems. Key parameters for monitoring include flow rate, turbidity, chemical oxygen demand (COD), total suspended solids (TSS), hydrocarbons, salinity, and pH. Flow sensors enable real-time measurement of volumetric throughput, facilitating hydraulic control and retention time optimization in treatment units. Turbidity and TSS sensors monitor particulate loads, critical for pre-treatment efficiency and fouling prevention in membranes or biofilm reactors. COD sensors provide information on organic matter concentration, allowing dynamic adjustment of biological or advanced oxidation processes. Hydrocarbon sensors detect oil-in-water concentrations, essential for oil separation, adsorption, and compliance with environmental discharge limits. Salinity sensors track total dissolved solids and ionic composition, informing anti-scaling strategies and chemical dosing. pH sensors monitor acidity or alkalinity, guiding neutralization and chemical adjustment in physicochemical units.

Integration of multiple sensor types enables a holistic understanding of PW quality, allowing operators to capture the complex interactions between water chemistry, biological activity, and treatment efficiency. Sensor networks can be deployed in both centralized and decentralized configurations, with placement optimized for influent streams, intermediate process units, and final effluent.

IoT technology enables continuous data transmission from sensors to local or cloud-based platforms. Each sensor can communicate via wired or wireless protocols, including LoRaWAN, Zigbee, Wi-Fi, or cellular networks, depending on site constraints. IoT connectivity supports real-time data visualization, remote monitoring, and automated alerts for operational deviations, such as sudden spikes in hydrocarbons, turbidity, or nutrient loads. In remote or offshore operations, IoT networks reduce reliance on on-site personnel and enable centralized management of multiple treatment units across distributed assets.

Raw sensor data often contain noise, outliers, or missing values due to sensor drift, fouling, environmental interference, or transmission errors. Effective data-driven optimization requires rigorous validation and cleaning strategies, including statistical filtering, range checks, and anomaly detection (Fowowe et al., 2025; Udechukwu, 2025). Data storage must be structured to facilitate rapid retrieval, historical analysis, and model training. Relational databases, time-series databases, or hybrid storage solutions are commonly employed, depending on the volume, velocity, and variety of data. Proper data management ensures that predictive models, AI algorithms, and performance dashboards operate on reliable and high-quality datasets.

The choice between edge and cloud computing has significant implications for latency, reliability, and operational efficiency. Edge computing involves processing data locally at the sensor or field unit level, enabling near-instantaneous decision-making for critical process adjustments, such as chemical dosing or aeration control. Edge processing reduces bandwidth requirements and enhances system resilience in off-grid or connectivity-limited environments. Cloud computing, on the other hand, centralizes data processing and storage, providing scalability, advanced analytics, machine learning model training, and integration with enterprise-level monitoring systems. Hybrid architectures that combine edge and cloud computing allow real-time control at the process level while supporting long-term trend analysis, predictive modeling, and optimization strategies at the supervisory level.

Data acquisition and digital monitoring are essential components of modern PW treatment optimization. Advanced sensor networks capture critical water quality and operational parameters, while IoT connectivity enables real-time data collection and remote oversight. Robust data validation, cleaning, and storage practices ensure reliable inputs for AI-driven predictive analytics and performance modeling. Edge and cloud computing provide complementary capabilities, enabling instantaneous operational adjustments and long-term optimization. Together, these technologies form the foundation for data-driven, adaptive, and resilient PW treatment systems, supporting energy-efficient operation, resource recovery, and circular water management in both onshore and offshore energy operations (Ihwughwavwe and Aniebonam, 2025; Olufemi et al., 2025).

2.4 AI- and Model-Based Performance Optimization

The complexity and variability of produced water (PW) in oil and gas operations present significant challenges for treatment infrastructure. Variations in salinity, hydrocarbons, total dissolved solids (TDS), nutrients, and suspended solids, coupled with fluctuating flow rates, make conventional control strategies inadequate for ensuring consistent effluent quality and efficient resource recovery. Artificial intelligence (AI) and model-based approaches offer a transformative pathway for optimizing PW treatment systems. By integrating machine learning, predictive modeling, and prescriptive analytics, operators can achieve real-time process optimization, predictive maintenance, and adaptive control, resulting in improved treatment performance, reduced energy consumption, and enhanced operational resilience (Adeshina and During, 2025; Udechukwu, 2025).

Machine learning (ML) algorithms are central to AI-driven optimization in PW treatment. Supervised learning models, such as random forests and support vector machines, can identify patterns in historical and real-time data, enabling the prediction of contaminant removal efficiency, fouling potential, or biofilm activity under varying operational conditions. Unsupervised learning techniques, including clustering and principal component analysis, facilitate anomaly detection, identifying deviations from expected system behavior that may indicate process inefficiencies, equipment malfunctions, or sudden spikes in contaminants. Predictive maintenance models leverage sensor data, process logs, and historical failure events to forecast the likelihood of membrane fouling, pump wear, or biofilm performance decline, allowing proactive intervention that reduces downtime and maintenance costs.

AI-based control enables dynamic adjustment of treatment process parameters to optimize system performance. Chemical dosing can be modulated in real time based on predicted contaminant load, minimizing excess use of coagulants, flocculants, or neutralizing agents. Membrane operation, including transmembrane pressure, flux, and cleaning cycles, can be adjusted to maintain high permeate quality while reducing energy consumption and membrane wear. Retention times in biological or hybrid treatment units can be optimized based on predicted organic load, nutrient content, and microbial activity, ensuring efficient nutrient assimilation, biofilm stability, and effluent quality. Bio-based treatment units, such as algal consortia or biofilm reactors, benefit from adaptive control, which aligns aeration, mixing, and light exposure with predicted growth and contaminant removal rates.

PW composition and flow rates exhibit substantial temporal and spatial variability, influenced by reservoir characteristics, water cut, production stage, and operational interventions. Scenario modeling allows operators to simulate system performance under a range of influent conditions, evaluating how treatment units respond to changes in salinity, hydrocarbons, nutrient loads, or total suspended solids. Computational models can integrate mechanistic process understanding with real-time data to generate probabilistic forecasts of effluent quality, fouling risk, and resource recovery potential (Michael and Ogunsola, 2025; Oparah et al., 2025). Scenario simulations support robust system design, enabling contingency planning, adaptive control, and rapid response to unexpected influent variability.

Predictive analytics provide forecasts of system behavior, while prescriptive analytics recommend operational adjustments to achieve specific objectives, such as minimizing chemical use, maximizing nutrient recovery, or maintaining effluent compliance. By combining predictive and prescriptive models, operators can implement automated control strategies that continuously optimize treatment performance. For example, if sensors detect a rise in TSS or hydrocarbons, the predictive model can forecast potential downstream impacts, and the prescriptive model can adjust coagulant dosing, membrane flux, or retention times in real time. Such integration enables decision support for both automated and operator-guided interventions, improving system efficiency and reducing human error.

AI- and model-based performance optimization transforms PW treatment from a reactive to a proactive process. Benefits include enhanced treatment efficiency, consistent effluent quality, energy and chemical savings, reduced operational downtime, and increased resource recovery from nutrients, biomass, and salts. The approach also facilitates modular and decentralized treatment designs, allowing scalable deployment in remote, off-grid, or water-stressed environments. Furthermore, the integration of AI enables continuous learning, where models are refined with accumulating operational data, improving predictive accuracy and system resilience over time.

AI- and model-based optimization represents a critical advancement for PW treatment infrastructure, enabling adaptive, data-driven control that addresses variability, operational inefficiencies, and energy-intensive processes. Through machine learning for pattern recognition, anomaly detection, and predictive maintenance, combined with dynamic process optimization, scenario modeling, and integrated predictive-prescriptive analytics, operators can achieve robust, efficient, and sustainable PW management (Okafor et al., 2025; Umoren, 2025). This approach supports resource recovery, circular water management, and environmental compliance, providing a practical pathway for next-generation PW treatment systems in modern oil and gas operations.

2.5 Resource Recovery and Reuse Integration

Produced water (PW) is no longer merely a waste stream in oil and gas operations; it is increasingly recognized as a resource-rich effluent with the potential for nutrient, biomass, and mineral recovery. Integrating resource recovery into PW treatment infrastructure enhances sustainability, reduces environmental impact, and supports circular water management. Effective integration requires understanding the composition of PW, optimizing treatment processes, and employing predictive and prescriptive models to guide recovery pathways. By combining physicochemical and bio-based treatments with digital monitoring and process optimization, energy operations can transform PW into valuable water, nutrients, biomass, and minerals while maintaining effluent quality suitable for reuse.

Nitrogen and phosphorus are key nutrients commonly present in PW due to reservoir conditions and injection fluids. Bio-based treatment units, such as biofilm reactors and algal consortia, can assimilate these nutrients, converting them into biomass while simultaneously reducing organic load and improving effluent quality. Nitrogen can be captured via nitrification-denitrification processes or ammonium assimilation, while phosphorus can be precipitated chemically or biologically incorporated into microbial or algal biomass. Organic matter, including dissolved organic carbon and volatile fatty acids, can be assimilated as a substrate for microbial growth, facilitating nutrient cycling and enhancing biological treatment efficiency (Amadi et al., 2025; Abah et al., 2025). Recovery of these nutrients reduces environmental discharge impacts and enables reuse as fertilizers or soil amendments, closing material loops in agricultural and industrial contexts.

Biomass generated during nutrient recovery and bio-based treatment presents additional value. Algal and bacterial biomass can be harvested and processed into bioenergy through anaerobic digestion or converted into biofertilizers and soil conditioners. Photobioreactors or high-rate algal ponds allow controlled growth of algal consortia using nutrients in PW as feedstock, producing significant biomass yields. Integrating biomass valorization into treatment systems not only supports circular economy objectives but also offsets energy and chemical costs by providing a renewable feedstock for energy production or soil enhancement. Harvesting strategies must account for salinity tolerance, light exposure, and hydraulic retention to optimize productivity and minimize operational complexity.

Salts and minerals constitute another recoverable resource from PW, particularly in high-salinity offshore or deep onshore reservoirs. Physicochemical processes such as evaporation, crystallization, and membrane concentration can extract sodium chloride, calcium, magnesium, and other valuable ions. Recovered salts can serve as industrial feedstock, water softening agents, or chemical precursors, while mineral recovery reduces the volume and environmental impact of brine disposal. Hybrid treatment systems, combining membranes with evaporation or crystallization units, allow simultaneous water purification and salt recovery, providing dual benefits of water reuse and material reclamation.

Data-driven modeling and scenario analysis are critical for optimizing resource recovery pathways. Mechanistic, empirical, or hybrid models can predict nutrient uptake, biomass production, and salt crystallization under variable PW composition and flow conditions. Machine learning algorithms and AI-enhanced models further enable adaptive control, allowing dynamic adjustment of process parameters such as chemical dosing, retention time, aeration, and light exposure to maximize recovery efficiency (Ike et al., 2025; David et al., 2025). Scenario modeling supports evaluation of different reuse pathways, including irrigation, industrial process water, or enhanced oil recovery, ensuring that recovered resources are applied effectively within a circular water management framework. Predictive models also facilitate decision-making regarding energy consumption, chemical inputs, and operational schedules, aligning resource recovery with environmental, economic, and regulatory objectives.

Integrating nutrient, biomass, and mineral recovery within PW treatment systems generates multiple benefits. It enables the transformation of PW from a waste liability into a resource stream, reduces freshwater demand, lowers environmental discharge risks, and supports sustainable industrial or agricultural reuse. Coupled with AI-based optimization and digital monitoring, resource recovery systems operate adaptively under variable PW characteristics, improving resilience and operational efficiency. Moreover, integration with modular and decentralized treatment units allows scalable deployment in remote or off-grid energy operations.

Resource recovery and reuse integration represents a paradigm shift in PW management. By recovering nutrients, biomass, and salts, and optimizing reuse pathways through modeling and AI-driven control, PW treatment systems can deliver environmental, operational, and economic benefits. These integrated approaches advance circular water management, reduce the environmental footprint of energy operations, and support the sustainable valorization of a previously underutilized resource stream, positioning PW as a strategic input for water, energy, and material efficiency in modern oil and gas operations.

2.6 Operational and Environmental Considerations

Produced water (PW) management in oil and gas operations presents a complex interplay of operational, environmental, and sustainability challenges. Treatment systems must address high variability in water composition, energy-intensive processes, and the need for consistent effluent quality, while minimizing environmental impacts. Integrating energy-efficient strategies, monitoring, and adaptive control is essential to ensure both operational resilience and environmental compliance (Giwah et al., 2025; Okuwobi et al., 2025). This examines the key operational and environmental considerations for modern PW treatment systems, with a focus on energy management, environmental footprint reduction, and risk mitigation strategies.

PW treatment systems are inherently energy-intensive. Physicochemical processes, such as membrane filtration, adsorption, and advanced oxidation, require continuous pumping, pressure control, and chemical dosing, while bio-based units like algal or biofilm reactors demand aeration, mixing, and lighting. In off-grid or remote operations, reliance on conventional diesel or grid electricity can increase operational costs and carbon emissions. Integrating renewable energy solutions such as solar photovoltaics, wind turbines, or hybrid energy systems can offset these energy demands and enhance sustainability. For example, solar-powered pumping and aeration units can supply reliable energy to treatment trains, while wind-hybrid systems provide redundancy and continuous operation in variable climatic conditions.

Energy optimization is also achieved through adaptive process control enabled by AI and digital monitoring. By dynamically adjusting chemical dosing, membrane flux, retention time, and aeration based on real-time water quality, energy consumption can be minimized without compromising treatment performance. Predictive models allow operators to schedule high-energy processes during periods of peak renewable generation, further reducing reliance on fossil fuels and decreasing operational carbon footprint.

Environmental considerations are central to sustainable PW management. Emissions associated with chemical use, pumping, and heating must be minimized through energy-efficient operation and selection of low-impact chemicals.

Treatment processes that produce residual waste streams, such as sludge, spent adsorbents, or concentrated brine, require careful handling and disposal to prevent soil and water contamination. Hybrid treatment systems integrating bio-based and physicochemical processes can reduce chemical requirements and associated emissions, while enabling nutrient recovery, biomass valorization, and salt reclamation.

The design of treatment systems must also account for water losses, potential odor emissions, and land footprint, particularly in remote or environmentally sensitive areas. Modular and compact treatment units reduce spatial requirements, while centralized control of chemical dosing and optimized retention times minimize residual waste production (Taiwo et al., 2025; Oyeboade et al., 2025). By adopting life-cycle assessment (LCA) approaches, operators can quantify environmental impacts across energy use, emissions, and waste generation, guiding design and operational decisions toward sustainable outcomes.

Operational reliability and environmental safety are closely linked in PW treatment. Sudden spikes in contaminant load, equipment failure, or process deviations can compromise effluent quality, disrupt resource recovery, and increase environmental risk. Digital monitoring and AI-enabled early warning systems play a critical role in risk mitigation. Real-time sensors measuring flow, turbidity, chemical oxygen demand (COD), total suspended solids (TSS), hydrocarbons, salinity, and pH provide continuous feedback on treatment performance. Predictive analytics detect anomalies, forecast potential system failures, and alert operators to operational deviations before they escalate.

For example, predictive models can identify early signs of membrane fouling or biofilm performance decline, enabling timely cleaning, maintenance, or operational adjustments. Automated alerts for contaminant spikes allow rapid intervention, reducing the risk of discharging untreated or partially treated water. Scenario modeling also supports contingency planning, guiding operators on optimal responses to extreme PW composition, equipment outages, or energy supply interruptions. Such proactive management ensures consistent effluent quality, protects downstream ecosystems, and minimizes regulatory compliance risks.

Optimizing operational performance while minimizing environmental impacts requires a holistic, integrated approach. Renewable energy integration, AI-driven process control, and digital monitoring collectively reduce energy consumption, emissions, and chemical usage. Hybrid treatment systems allow simultaneous recovery of nutrients, biomass, and salts, further minimizing residual waste and promoting circular water management. Risk mitigation through predictive analytics and early warning systems enhances operational reliability, ensuring that both environmental and production objectives are met.

Operational and environmental considerations are central to the design and management of modern PW treatment systems. Energy-efficient strategies, including off-grid renewable energy integration and adaptive AI-enabled control, reduce operational costs and carbon footprint. Minimizing chemical use, residual waste, and emissions mitigates environmental impacts, while digital monitoring and predictive risk management ensure reliable system performance and effluent compliance (Ajirotutu et al., 2024; Oyeyemi et al., 2024). By integrating these strategies, PW treatment infrastructure can operate sustainably, supporting both resource recovery and environmental protection in energy operations, particularly in remote or water-stressed regions. These approaches position PW treatment as a proactive, resource-efficient, and environmentally responsible component of modern oil and gas operations.

2.7 Pilot Modeling Applications

The integration of data-driven monitoring and model-based optimization in produced water (PW) treatment has been increasingly demonstrated in both onshore and offshore oil and gas operations. Pilot projects and case studies highlight the practical feasibility of combining digital sensors, artificial intelligence (AI), and predictive modeling to improve treatment efficiency, enable resource recovery, and reduce energy consumption. These applications provide valuable insights into operational performance, technology integration, and scalability, offering a roadmap for broader implementation in diverse energy contexts.

In onshore oilfields, pilot-scale treatment facilities have implemented digital sensor networks for real-time monitoring of flow rate, salinity, turbidity, total suspended solids (TSS), chemical oxygen demand (COD), and hydrocarbons. For example, a North American shale oil pilot integrated a modular hybrid treatment train combining membrane filtration, adsorption, and algal biofilm reactors with IoT-enabled monitoring and machine learning algorithms for dynamic process control. The system achieved significant improvements in treatment efficiency, with total organic carbon removal exceeding 85%, and consistent compliance with regulatory discharge standards. Predictive modeling allowed optimization of chemical dosing and membrane cleaning cycles, reducing energy consumption by approximately 20% compared with conventional manual operation (Falana et al., 2024; Odezuligbo et al., 2024). Additionally, the integration of bio-based treatment facilitated nitrogen and phosphorus recovery through algal assimilation, providing biomass for potential bioenergy and soil amendment applications.

Another onshore in the Middle East focused on the adaptive control of high-salinity PW from a mature oilfield. Machine learning models forecasted spikes in TDS and hydrocarbon loads, enabling preemptive adjustments in membrane flux, coagulant dosing, and retention time. This proactive approach minimized fouling, stabilized effluent quality, and enhanced overall resource recovery, demonstrating the value of predictive analytics in highly variable PW conditions.

Offshore PW treatment presents additional challenges, including limited space, high salinity, and operational constraints in remote platforms. Pilot studies in the North Sea employed AI-driven monitoring to optimize compact membrane-adsorption units integrated with biofilm reactors. Sensors captured real-time salinity, hydrocarbons, TSS, and nutrient concentrations, while predictive algorithms adjusted operational parameters to maintain consistent effluent quality despite fluctuating water cuts and hydrocarbon content. Performance outcomes included over 90% hydrocarbon removal, stable nutrient uptake, and a 15–25% reduction in energy use by dynamically optimizing pump operation and aeration rates. The offshore pilots also demonstrated the potential for automated early warning systems, which detected membrane fouling and contaminant spikes, allowing timely corrective actions that minimized downtime and environmental risk.

Across both onshore and offshore pilots, data-driven and model-based approaches consistently improved treatment efficiency, stabilized effluent quality, and enhanced resource recovery. Algal and biofilm-based nutrient assimilation recovered significant fractions of nitrogen and phosphorus, while biomass harvesting provided feedstock for bioenergy or fertilizers. Salt and mineral recovery was optimized through scenario modeling, enabling the integration of physicochemical processes with energy-efficient evaporation and crystallization units (Ajirotutu et al., 2024; Okuwobi et al., 2024). Energy savings were achieved through predictive control of pumps, chemical dosing, and aeration, with reported reductions of 15–25% compared to static operational schedules.

Key lessons from these emphasize the importance of modularity, adaptability, and integration. Hybrid treatment trains that combine physicochemical and bio-based processes provide flexibility to treat variable PW composition and flow rates. Data quality is critical: robust sensor calibration, validation, and cleaning protocols are essential for accurate predictive modeling. Pilot projects also highlighted the necessity of edge-cloud hybrid computing architectures, enabling rapid local adjustments while supporting long-term trend analysis and machine learning model refinement.

Scalability potential is high, particularly for modular units capable of incremental capacity expansion in both remote onshore and offshore contexts. Scenario modeling supports planning for diverse PW compositions and operational contingencies, while predictive and prescriptive analytics ensure adaptive management at larger scales. Integration of AI and digital monitoring allows operators to maintain efficiency, resource recovery, and environmental compliance as systems expand.

Pilot modeling applications demonstrate that data-driven PW treatment infrastructure can achieve substantial improvements in treatment efficiency, energy consumption, and resource recovery. Onshore and offshore pilots reveal the value of integrating sensor networks, AI-driven optimization, and predictive modeling in adaptive hybrid treatment systems. Lessons learned underscore the importance of modularity, robust data management, and scenario-based modeling for scalability. Collectively, these studies validate the conceptual framework for data-driven PW treatment optimization and provide a practical pathway toward sustainable, efficient, and resilient water management in energy operations.

2.8 Research Gaps and Future Directions

Despite significant advancements in data-driven monitoring, AI-enabled control, and predictive modeling for produced water (PW) treatment, several critical research gaps remain that must be addressed to enable widespread deployment, robust operational performance, and integration into circular water management strategies. Addressing these gaps will enhance system reliability, sustainability, and scalability across diverse onshore and offshore energy operations.

While laboratory and pilot-scale studies have demonstrated the potential of data-driven PW treatment systems, long-term field validation is limited. Most studies report operational performance over weeks to months, leaving uncertainties regarding system resilience under prolonged exposure to variable water composition, fluctuating flow rates, extreme temperatures, and operational contingencies. Extended pilot-scale deployments are needed to evaluate the durability of sensor networks, predictive models, and AI-driven control strategies. Long-term field data will inform adaptive maintenance schedules, assess membrane fouling rates, biofilm stability, chemical dosing efficiency, and energy consumption under real-world conditions. These deployments will also provide critical insight into the cumulative performance of hybrid treatment systems integrating physicochemical and bio-based units, including nutrient recovery, biomass harvesting, and salt or mineral extraction.

A major barrier to widespread adoption of AI-enabled PW treatment is the lack of standardized modeling protocols and integration frameworks. Current approaches vary widely in terms of sensor selection, data acquisition frequency, machine learning algorithms, predictive modeling methods, and integration with process control. Standardization is necessary to ensure reproducibility, reliability, and interoperability of models across different treatment configurations, field conditions, and regulatory environments (Onotole et al., 2022; John, A.O. and Oyeyemi, 2022). Guidelines for sensor calibration, data validation, cleaning procedures, and model training are essential to reduce bias, minimize uncertainty, and enable consistent performance across multiple sites. Additionally, standardized interfaces for integrating predictive and prescriptive analytics with hybrid treatment units will enhance system adaptability and facilitate technology transfer.

PW treatment systems must be designed for adaptive operation to handle temporal and spatial variability in water composition, flow rate, and operational disruptions. Research is needed to develop modular, flexible architectures capable of adjusting chemical dosing, retention time, aeration, membrane operation, and biofilm or algal growth dynamically based on predictive insights. Coupling these adaptive systems with renewable energy sources, including solar, wind, or hybrid off-grid solutions, presents an additional challenge. Energy-constrained sites require optimization strategies that align process control with available energy, balancing treatment performance, resource recovery, and operational reliability. Investigating energy-efficient adaptive designs and developing integrated energy-water optimization algorithms are critical next steps.

Data-driven PW treatment can advance circular water management by integrating predictive analytics with resource recovery pathways. AI offers the potential to optimize nutrient recovery, biomass harvesting, and salt or mineral extraction while simultaneously enabling fit-for-purpose water reuse for irrigation, industrial processes, or enhanced oil recovery. However, research is needed to quantify trade-offs between treatment efficiency, energy consumption, and resource recovery under variable PW conditions. Scenario modeling and AI-driven simulations can support decision-making for implementing circular water strategies, ensuring both environmental compliance and operational efficiency. Further, the integration of real-time feedback and adaptive prescriptive analytics can enable proactive allocation of recovered resources, closing material loops and promoting sustainable water stewardship (Aniebonam, 2024; Ajirotutu et al., 2024).

Future research should focus on large-scale pilot projects and long-term operational monitoring to validate AI-driven treatment strategies under real-world conditions. Development of standardized modeling frameworks, including sensor calibration, data preprocessing, and machine learning protocols, is essential for reproducibility and regulatory acceptance. Energy-aware adaptive system design and integration with renewable energy sources will enhance operational resilience in off-grid or resource-constrained settings. Finally, exploring the synergistic integration of predictive and prescriptive analytics for circular water management will enable simultaneous optimization of treatment efficiency, resource recovery, and sustainability outcomes.

Addressing these research gaps will accelerate the deployment of robust, adaptive, and sustainable PW treatment systems. Long-term field validation, standardization of modeling protocols, adaptive design, renewable energy integration, and AI-enabled circular water strategies collectively represent the future direction for data-driven PW management. Advancing these areas will support environmental compliance, operational efficiency, and resource recovery, transforming PW treatment infrastructure into a resilient, sustainable, and resource-oriented component of modern oil and gas operations (Oyeyemi et al., 2024; Falana et al., 2024).

CONCLUSION

The conceptual modeling framework for data-driven produced water (PW) treatment optimization integrates real-time monitoring, predictive analytics, and adaptive control to address the complex and variable nature of PW in oil and gas operations. By combining sensor networks for flow, turbidity, salinity, chemical oxygen demand (COD), total suspended solids (TSS), hydrocarbons, and pH with IoT-enabled connectivity and machine learning algorithms, the framework enables continuous performance assessment, anomaly detection, and predictive maintenance. Modeling tools—ranging from mechanistic process simulations to AI-driven predictive and prescriptive analytics—allow operators to optimize chemical dosing, membrane operation, retention time, and bio-based treatment processes in response to fluctuating PW composition and flow rates. Scenario modeling further enhances resilience by simulating system behavior under variable operational and environmental conditions, guiding robust treatment system design and decision-making.

Strategically, this framework provides multiple benefits. Operational efficiency is enhanced through energy optimization, dynamic process control, and reduction of downtime, while resource recovery is maximized via nutrient assimilation, biomass harvesting, and salt or mineral reclamation. Integration with bio-based and hybrid treatment processes supports sustainable management of organic load and contaminants, contributing to environmental protection. The framework also aligns with circular water management principles by enabling fit-for-purpose reuse of treated water for industrial processes, irrigation, or enhanced oil recovery, effectively transforming PW from a waste liability into a resource stream.

The conceptual framework has significant implications for scaling and broader deployment. Modular and adaptive system designs facilitate incremental expansion and allow customization to variable PW characteristics across onshore and offshore sites. Standardized data-driven modeling protocols support reproducibility, interoperability, and regulatory compliance, ensuring consistent effluent quality and adherence to environmental standards. Moreover, the integration of renewable energy sources and predictive maintenance strategies enhances sustainability and resilience in remote or off-grid operations.

The data-driven conceptual modeling framework offers a comprehensive, proactive, and sustainable approach to PW treatment. By combining real-time monitoring, AI-enabled optimization, and resource recovery strategies, the framework provides a pathway for efficient, environmentally responsible, and scalable PW management, supporting operational performance, regulatory compliance, and long-term sustainability in the energy sector.

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