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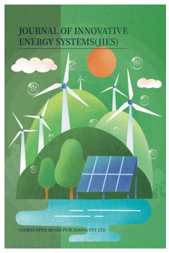

Review

Optimization in the Oil and Gas Industry: A Review of Techniques, Trends, and Scientific Advances

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Abstract

The oil and gas industry is undergoing a transformative shift driven by the pursuit of operational efficiency, environmental responsibility, and technological innovation. This review critically analyzes optimization strategies deployed across upstream, midstream, and downstream operations. Drawing from recent advances, it explores the integration of feedback control systems, machine learning algorithms, and digitalization tools such as digital twins and edge computing. The review highlights how traditional PID-based control logic has evolved to support real-time optimization, while artificial neural networks (ANNs) have emerged as effective alternatives to physics-based models, particularly in artificial lift and reservoir management. A key finding is the centrality of robust data governance in ensuring the reliability and sustainability of optimization outcomes. Quantitative studies confirm that digital investment, when aligned with organizational restructuring, significantly enhances energy efficiency and production performance. The review also identifies persistent barriers, including corporate resistance to automation and technical misalignment between optimization layers. Emerging trends such as hybrid energy systems and multidimensional optimization frameworks reflect the industry's growing alignment with environmental and social sustainability goals. This synthesis provides practical insights and a forward-looking perspective on the tools and strategies delivering measurable value in oil and gas optimization under real-world constraints.

Keywords

Digitalization, Energy efficiency, Optimization, Process control, Sustainability

Article History

Received: 07 July 2025 Revised: 14 August 2025

Accepted: 22 August 2025 Available Online: 03 September 2025

1. Introduction

The oil and gas industry remains a cornerstone of global energy supply, underpinning economic development and industrial productivity across the world. As the industry evolves, it faces intensifying demands to enhance operational efficiency, minimize environmental impacts, and meet rising sustainability expectations across all phases of production and distribution [1]. In response to these challenges, optimization has emerged as a fundamental engineering discipline aimed at improving system performance and resource utilization throughout the upstream, midstream, and downstream segments of the petroleum value chain [2]. The growing importance of sustainability metrics and energy efficiency in oil and gas operations has been widely acknowledged in recent literature [3,4]. These studies highlight that the integration of environmental considerations into operational strategies, such as the use of green resource planning frameworks within oilfield microgrids, can improve reliability indices and reduce emissions across energy-intensive processes. Against this backdrop, this review evaluates current optimization practices in the oil and gas sector, focusing on their scientific basis, real-world applications, and the technological advancements driving this transformation. The analysis is grounded in recent empirical studies that demonstrate the measurable benefits of advanced optimization tools. For instance, implementation of feedback control systems has led to a four percent increase in production from gas-lifted wells while simultaneously reducing equipment downtime and improving system responsiveness [5]. Additionally, quantitative models based on production function analysis have established strong correlations between digital investment and energy efficiency, offering a valuable framework for strategic resource allocation [6].

The progression of optimization methodologies reflects broader trends in industrial digitalization. Traditional approaches, which often relied on periodic model-based simulations and steady-state assumptions [7], are gradually giving way to data-centric methods that incorporate machine learning algorithms and Internet of Things (IoT) enabled monitoring platforms [8]. These innovations support continuous optimization by adapting to real-time variability in reservoir and equipment behavior, as exemplified in modern electric submersible pump (ESP) control systems [5]. Nevertheless, practical implementation challenges persist. Computational complexity remains a major barrier in the deployment of large-scale optimization models [9], while the quality and consistency of field data continue to influence the effectiveness of decision-making processes [10]. These issues call for a balanced optimization approach that combines theoretical rigor with operational feasibility. Although progress has been achieved, there are notable gaps in existing research that limit the broader adoption of intelligent optimization systems. Classical control structures, such as those formulated in early plantwide optimization theories [11,12], emphasized the role of model-based strategies but often did not account for the challenges posed by dynamic reservoir conditions and limited real-time data availability [13]. While some studies have acknowledged these issues [7,9], many have not sufficiently explored how recent advances in artificial intelligence, particularly machine learning and artificial neural networks (ANNs), can address these limitations. Furthermore, previous contributions to the static versus dynamic optimization debate [8] have generally excluded ANN-based control models, thereby restricting their practical relevance in today’s operational environments.

This review builds upon these foundational studies by incorporating state-of-the-art machine learning and ANN methods into a broader optimization framework. By synthesizing diverse strands of current research, it offers an interdisciplinary perspective that unites fields often treated separately, including digital twins, edge computing, predictive analytics, and data governance systems. These components are examined not as standalone innovations but as part of an integrated strategy for advancing next-generation oilfield operations. The manuscript further explores how the industry is leveraging these emerging technologies to respond to evolving technical, environmental, and economic challenges. It evaluates the application of machine learning in reservoir modeling and property prediction, the deployment of advanced control structures for production optimization, and the growing use of digital twins for predictive asset management. By combining insights from academic literature and real-world field implementations, this review provides actionable knowledge for engineers, researchers, and policymakers seeking to identify the most effective optimization tools under real-world operational constraints. In doing so, it also highlights the potential areas for future research and innovation that could enable further improvements in energy efficiency, sustainability, and operational resilience within the global oil and gas sector.

2. Methodology

This review as displayed in Figure 1 followed a structured scoping methodology adapted from the frameworks proposed by Arksey and O’Malley [14] and Snyder [15] to systematically map the landscape of optimization strategies in the oil and gas sector. The approach involved a multi-phase process of identification, screening, eligibility assessment, and thematic synthesis of relevant literature. The objective was to capture the breadth and depth of recent advancements in optimization practices, with particular focus on automation, machine learning applications, reservoir management, and energy efficiency. Relevant literature was sourced from peer-reviewed journals, conference proceedings, and technical reports published between 2000 and 2025. Searches were conducted using Boolean operators across academic databases including Scopus, IEEE Xplore, and ScienceDirect. Search terms included combinations such as “oil and gas”, optimization”, “machine learning in reservoir”, “digital twin AND production”, and “process control AND automation”.

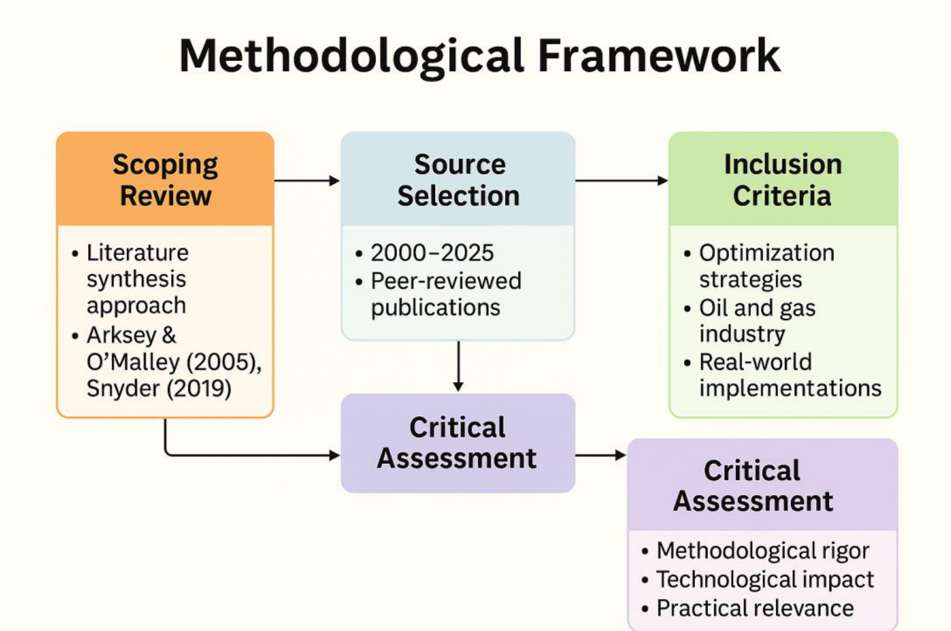

Figure 1. Scoping review of optimization strategies in the oil and gas industry.

The inclusion criteria prioritized studies that reported quantitative outcomes, demonstrated real-world field implementations, or introduced novel digital technologies applicable to upstream, midstream, or downstream oil and gas operations. Studies were excluded if they lacked empirical validation, were limited to purely theoretical modeling, or did not contribute substantial new insights to the optimization discourse. However, theoretical models were retained where they introduced innovative concepts with potential for application. A total of 75+ articles were retained after duplicate removal and relevance screening. These were thematically analyzed based on methodological rigor, technological innovation, integration of data governance principles, and relevance to industrial practice. The final synthesis incorporated cross-comparison of optimization domains and highlighted emerging interdisciplinary trends in digital oilfield optimization.

3. Result and Discussion

3.1 Optimization Through Feedback Control and Automation

Process control stands as a fundamental pillar of optimization in oil and gas operations, serving both regulatory and economic functions. For decades, conventional Proportional Integral Derivative (PID) controllers have reliably maintained critical setpoints for pressure, temperature, and flow rates. Recent research by Krishnamoorthy et al. [5] demonstrates how these simple feedback structures can be strategically deployed for optimal operation, often eliminating the need for complex model-based optimization tools. They demonstrated that a carefully selected set of controlled variables within simple feedback loops can deliver near-optimal results even under disturbances, thus reducing reliance on computationally expensive re-optimization. Unlike AI-based systems, they emphasize the practicality of self-optimizing control strategies that offer simpler, more transparent solutions with comparable field performance. This finding is supported by Foss et al. [8], who showed how traditional control structures can systematically replace more complex optimization algorithms while maintaining economic performance. The principle of self-optimizing control provides a powerful framework for maintaining near-optimal operation without continuous optimization interventions. As articulated by Skogestad [11] and further developed by Halvorsen et al. [13], this approach relies on identifying controlled variables that inherently keep the process close to its economic optimum. These concepts build upon foundational work by Morari et al. [12], who first established the theoretical connection between feedback control and economic optimization, creating a basis for modern control strategies that remains relevant today.

Compelling evidence from Krishnamoorthy and Skogestad [16] shows that optimal production can be achieved through PID controllers combined with selector logic and constraint tracking mechanisms. These control architectures dynamically redistribute control authority as operational constraints change. Darby et al. [7] further highlight how the time required for model updates and optimization calculations often renders these approaches impractical for real-time decision making. These limitations have driven growing interest in feedback-based approaches that can automatically adapt to system variability, as demonstrated in field implementations [17]. Practical applications validate this approach, demonstrating successful implementations where control systems automatically adjust gas lift allocations and manage production under challenging conditions like gas coning [18,19]. The evolution of control system architectures continues to expand optimization possibilities. However, traditional model-based optimization approaches face significant challenges in oilfield applications [19]. Campos et al. [9] observed that oil production environments frequently exhibit dynamics and uncertainties that challenge the reliability of steady-state models.

Takacs [20] documents advanced applications in ESP systems, where sophisticated control logic maintains optimal operating points while respecting equipment constraints. Similarly, Reyes Lúa et al. [21] have shown how straightforward logic can optimally manage gas injection rates based on real-time well performance. These developments reflect the industry's growing recognition of control systems as active optimization tools rather than mere regulatory devices, marking a significant shift in operational philosophy.

3.2 Data-Driven Optimization and Machine Learning Applications

The integration of data-driven technologies, particularly ANNs and broader machine learning models, has significantly advanced optimization capabilities across oil and gas operations. These tools offer flexible and adaptive alternatives to traditional rule-based systems, especially in domains such as artificial lift optimization, equipment diagnostics, and property prediction under uncertain and nonlinear conditions. At the core of ANN functionality lies a computational architecture inspired by biological neurons, consisting of interconnected layers: input, hidden, and output nodes. Each connection is assigned a weight that adjusts during the training phase to minimize the error between predicted and actual outputs. Most applications in oilfield optimization employ feedforward multilayer perceptron (MLP) architectures, trained using algorithms such as backpropagation or the Levenberg–Marquardt optimization method due to their efficiency in handling nonlinear and noisy datasets [22]. These models are particularly effective in learning complex relationships between operational parameters like wellhead pressure, gas injection rates, and production volume without relying on explicit physical equations.

Model selection depends on the task. MLP is widely used for continuous function approximation, while radial basis function (RBF) networks are preferred for pattern classification in fault detection scenarios. Support vector machines (SVM) also find use in classification and regression tasks due to their robustness against overfitting in high-dimensional spaces. Recent reviews suggest that hybrid models combining ANN with fuzzy logic or evolutionary algorithms further enhance predictive performance in complex reservoir conditions. Successful deployment of Machine Language (ML) models begins with data preprocessing. This includes outlier removal, normalization of input variables, and feature engineering to reduce dimensionality and improve model generalization. For example, in gas lift optimization, features such as flowline pressure, gas injection rate, and temperature are normalized and smoothed before being introduced into the ANN model [21,23,24]. Preprocessing ensures that the network can learn relevant patterns without being misled by noise or inconsistent measurements [25].

Training, validation, and testing of models are conducted using historical operational datasets, typically divided into three subsets. The training phase involves adjusting network weights based on known inputs and outputs. Validation helps to prevent overfitting by evaluating the model on unseen data during training. Final testing assesses model performance on completely separate data. Common performance metrics include the root mean squared error (RMSE), mean absolute error (MAE), and coefficient of determination (R^2). In recent case studies, ANN models have achieved R^2 values above 0.95 in gas lift optimization tasks, demonstrating their suitability for real-time field deployment [21,23]. Beyond control and diagnostics, ML and ANN techniques are increasingly used for reservoir property prediction. These models are applied to estimate critical physical properties such as dew point pressure, bubble point pressure, gas compressibility factor (Z-factor), formation volume factor (FVF), and crude oil viscosity. For example, advanced models trained on pressure-volume-temperature (PVT) data have shown improved prediction accuracy of crude oil viscosity and gas solubility, especially when using deep learning structures that incorporate physical constraints [26]. Another study demonstrated that SVM and ANN methods can accurately model FVFs across different pressure and temperature regimes, outperforming conventional correlations [27].

The novelty of ANN and ML applications in oil and gas lies in their ability to support real-time decision-making under uncertainty. Unlike static models that require periodic recalibration, intelligent algorithms can continuously adapt to incoming data, improving their predictive accuracy over time. This adaptability is especially important in mature fields with heterogeneous reservoirs and marginal wells, where traditional physics-based models often fail to account for field dynamics [24]. Additionally, ANN systems embedded in digital twin architectures enhance operational visibility by enabling predictive simulations and proactive maintenance planning [28,29]. Moreover, ML tools enable condition monitoring and fault detection in critical systems such as compressors, pumps, and separators. By analyzing deviations from learned operational baselines, ANN models can issue early warnings of equipment failure, reducing downtime and maintenance costs [5,30]. Their ability to generalize from past patterns makes them valuable in offshore and remote environments where manual diagnostics are limited by access or safety considerations.

3.3 Machine Learning Applications in Reservoir Property Prediction

The application of machine learning to reservoir property prediction has become a vital tool for enhancing production forecasting, flow assurance, and overall reservoir management. Traditional empirical models often fail to capture the nonlinear and high-dimensional dependencies that exist among pressure, temperature, and fluid behavior, particularly in unconventional or marginal fields. In contrast, ANNs, SVMs, and hybrid intelligent systems offer flexible frameworks capable of learning complex functional relationships directly from data, without the need for explicit physical modeling.

Among the most frequently predicted properties using machine learning approaches are dew point and bubble point pressures, FVF, crude oil viscosity, Z-factor, and CO_2 solubility. For instance, ANN models trained on PVT datasets have demonstrated exceptional accuracy in predicting bubble point pressure and oil viscosity across wide operating ranges [31,32,26]. These models are capable of generalizing across diverse geologic settings and can be retrained as new data becomes available, which enhances their long-term utility in dynamic reservoir simulation environments.

Support vector regression and hybrid ANN-genetic algorithm models have also proven effective in modeling gas compressibility and Z-factor, particularly in dry gas and retrograde condensate reservoirs [27]. These machine learning methods outperform traditional correlations in terms of both accuracy and robustness, especially under extreme pressure and temperature conditions where conventional models often fail. The advantage of data-driven models extends beyond accuracy. These tools are highly tolerant to data imperfections, such as sensor noise, missing values, and operational anomalies, which are common in mature and brownfield assets [10,24]. By learning from field data, these models offer a more adaptable and scalable solution for predicting key fluid properties under varying operational scenarios. When integrated into digital twin frameworks and real-time optimization systems, machine learning models allow continuous updates of property estimates based on live input data. This capability enables proactive adjustments in operational strategies, contributing to improved hydrocarbon recovery, reduced energy consumption, and better overall field performance [6,33,34]. Such integration represents a critical step toward the realization of closed-loop, self-optimizing oilfield systems.

3.4 Reservoir Management and Production Allocation Optimization

Reservoir management represents a critical strategic function in upstream oil and gas operations, balancing hydrocarbon recovery optimization with economic viability and reservoir integrity preservation. This complex process coordinates production rates, fluid injection strategies, and resource distribution across multiple wells and facilities to maximize asset value throughout the reservoir lifecycle. As Krishnamoorthy et al. [5] demonstrated, modern reservoirs particularly those with unconventional or heterogeneous formations demand sophisticated optimization frameworks that account for both subsurface dynamics and surface system interactions. Production allocation presents unique optimization challenges, requiring careful management of well interference effects, gas lift distribution, and surface processing constraints while maintaining compliance with operational and regulatory boundaries. Traditional approaches using iterative methods like Newton iteration often struggle with real time operational variability due to their sensitivity to input assumptions. These limitations have driven the development of more robust optimization techniques [35]. Recent advances in investment strategy for upstream oil and gas projects emphasize risk-aware portfolio planning techniques that account for regulatory shifts and volatile price conditions [29,36,37]. These optimization approaches are increasingly embedded within broader energy portfolio strategies that account for diversification, hedging trade-offs, and integrated asset governance [38-40].

Advanced mathematical programming methods have significantly improved allocation optimization. Beckner and Davidson [29] pioneered sequential quadratic programming approaches that incorporate nonlinear multiphase flow dynamics and allow for penalty terms related to cost, emissions, and equipment degradation. Kosmidis et al. [35] expanded this work through mixed integer nonlinear programming (MINLP), enabling simultaneous optimization of well rates, lift gas allocation, and facility utilization while accurately modeling pressure drops and manifold constraints. Their integrated approach proved particularly valuable in mature fields with complex flow networks. While powerful, MINLP methods face computational challenges at field scale, prompting alternative approaches. Ray and Sarker [41] developed a multi objective gas lift optimization framework that balances production volume, gas usage efficiency, and equipment constraints while maintaining solution stability. This work has been complemented by recent machine learning applications, such as the ANN models that predict optimal production responses by learning from historical well behavior, enabling rapid scenario analysis without full physics simulations [21].

Marginal and brownfield developments present special optimization challenges, particularly regarding gas lift constraints. Rashid [42] addressed these through constraint coupled algorithms that dynamically adjust injection rates based on marginal productivity, surface capacity, and gas availability. Such approaches prove invaluable for real time field management where operational changes require continuous strategy adjustments. Data quality and integration remain fundamental to optimization effectiveness. Comprehensive data governance frameworks are essential for maintaining consistency across seismic interpretations, well logs, flow measurements, and production reports. Without such integration, optimization decisions risk being suboptimal or erroneous. Emerging decentralized approaches offer promising alternatives to traditional centralized optimization [10,7]. Self-optimizing control structures with feedback mechanisms can maintain near optimal operation by responding to active constraints like maximum drawdown pressure or separator limits. These methods reduce computational burdens while improving responsiveness to system uncertainty [5,8].

3.5 Digital Transformation for Energy Efficiency and Resource Conservation

The oil and gas industry is experiencing a fundamental transformation through the convergence of operational and information technologies, marking its transition into the Fourth Industrial Revolution. This shift, characterized by widespread digitalization, IoT adoption, and advanced analytics, is reshaping how companies approach energy efficiency and resource conservation. As Shinkevich et al. [6] demonstrated through their comprehensive study, digital transformation serves as both an economic imperative and environmental necessity, enabling smarter resource utilization across the petroleum value chain while addressing sustainability challenges. Using Cobb-Douglas production functions established clear correlations between digital investments and operational improvements. Their research revealed that strategic expenditures in automation, real-time monitoring, and cloud integration yield measurable reductions in both energy intensity and operational costs [6]. As shown in Figure 2, strategic investments in digital technologies exhibit a strong positive correlation with energy efficiency improvements and operational cost reductions.

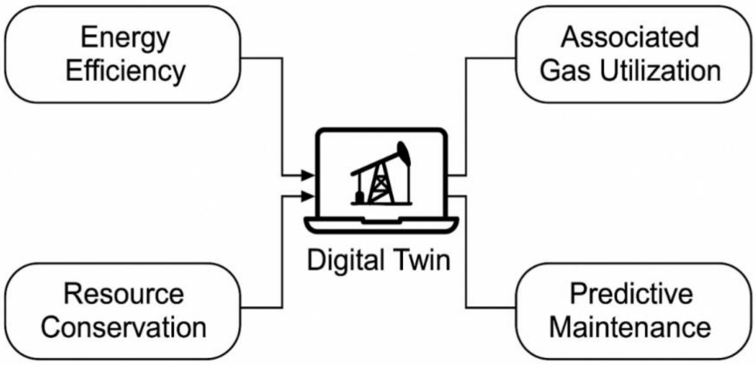

Figure 2. Correlation between digital investment levels and operational efficiency based on Cobb-Douglas regression analysis.

Importantly, the study highlighted that maximum efficiency gains occur when digitalization initiatives are implemented alongside workforce training and organizational restructuring, suggesting that human factors remain critical in digital transformation success [1]. The foundation for effective digital optimization lies in robust data governance. Extensive field research across South African oil operations, documenting how fragmented data systems undermine energy efficiency efforts. His work established that integrated data management platforms are essential for maintaining optimization benefits throughout the asset lifecycle, from exploration through production [10]. These findings were reinforced by Darby et al. [7], who showed that standardized data architectures can reduce decision latency by up to 40% in complex operational environments. These findings are further supported by Begishev et al. [43], who argue that the ethical, environmental, and technological implications of robotics and digital platforms must be critically assessed alongside technical performance metrics. One of the most impactful applications of digitalization is in associated petroleum gas (APG) management. Digital monitoring and control systems transform APG from a waste product into a valuable resource through reinjection, power generation, or liquefaction. Modern IoT-enabled gas measurement systems combined with adaptive control algorithms have demonstrated flare reduction efficiencies exceeding 85% in field trials. This technological progress supports both environmental compliance and economic optimization of gas utilization [6].

As noted by Barzegar et al. [4], incorporating virtualized green resource platforms within oilfield microgrids can enhance reliability and lower emissions, reinforcing the sustainability potential of digital optimization. Digital twin technology represents another breakthrough in energy optimization. Documented case studies where virtual asset replicas enabled predictive maintenance and production optimization in offshore environments. These digital twins integrate real-time sensor data with physics-based models to simulate equipment performance under various operating scenarios, allowing engineers to identify energy savings opportunities without physical intervention. The implementation of these technologies spans the entire hydrocarbon value chain. In upstream operations, cloud-based analytics platforms process drilling data to optimize well placement and completion designs. Midstream applications include smart pipeline monitoring systems that minimize energy losses during transportation. Downstream, AI-enhanced supervisory control and data acquisition (SCADA) systems dynamically adjust refining processes based on real-time feedstock quality and market demands [44,45].

Edge computing has emerged as a critical enabler for remote operations. By processing data locally at production sites, these systems maintain functionality even with limited connectivity while reducing the energy burden of continuous cloud data transmission [22]. This capability proves particularly valuable in distributed oilfield operations where reliable communication infrastructure may be lacking. Looking forward, the integration of renewable energy sources into oilfield operations presents new optimization challenges and opportunities. Recent pilot projects have demonstrated how machine learning can balance hydrocarbon production with solar or wind power generation, creating hybrid energy systems that reduce overall carbon intensity [24]. These innovations point toward a future where digital technologies enable the petroleum industry to meet both economic and environmental objectives.

3.6 Data Governance and Lifecycle Integration

Optimization success depends not only on advanced algorithms but equally on the quality, accessibility, and governance of operational data. Effective data governance establishes the framework ensuring data integrity, security, and relevance across all operational and strategic workflows. Comprehensive data governance directly enables optimization throughout the oil and gas production lifecycle, from exploration to abandonment. The upstream sector generates immense volumes of structured and unstructured data through seismic interpretation, drilling operations, and real-time equipment monitoring [10]. Continuous assessment of data quality attributes including accuracy, timeliness, and completeness which is essential for maintaining optimization effectiveness. Their research revealed that inconsistent data standards between departments can lead to suboptimal decisions with significant economic consequences [7,46].

Data governance framework emphasizing the synchronization of organizational processes, technological systems, and workforce competencies. The study found that companies implementing standardized data formats and cross-functional communication protocols achieved 30% faster decision cycles compared to those with fragmented data silos [10]. These governance structures prove particularly valuable during critical phase transitions, such as moving from exploration to development. Ellis et al. [47] further elaborates on the role of supplier relationship management in maintaining a resilient and collaborative data ecosystem, emphasizing how trust-based governance models can improve optimization performance across distributed operations. Beyond operational efficiency, robust data governance supports regulatory compliance and environmental stewardship. Centralized data repositories enhance risk management for well integrity monitoring and emissions reporting. When combined with real-time analytics platforms, these systems enable proactive optimization that considers both economic and sustainability objectives [1,48].

3.7 Optimization Challenges and Human Factors

Despite remarkable technological progress, organizational and human factors continue to constrain optimization adoption in oil and gas operations. Identified corporate culture and technical competency gaps as primary barriers, with field operators often preferring familiar manual processes over automated optimization systems perceived as opaque or inflexible [5]. The sustainability of optimization systems represents another critical challenge. Nearly 40% of advanced optimization applications are abandoned within three years due to insufficient maintenance and knowledge transfer [33]. For example, in many offshore operations, model predictive control systems installed, though successfully implemented, were later shut down due to the lack of trained personnel, poor documentation, or limited understanding of control objectives among new operators. This attrition frequently occurs when specialized personnel depart without establishing adequate documentation or training protocols. Similar concerns are raised in recent studies on the fragility of optimization frameworks in volatile economic conditions. Fattahi and Nafisi-Moghadam [49] demonstrate how external shocks such as oil sanctions reshape the interdependencies within financial systems, indirectly impacting optimization investment and resilience strategies in the petroleum sector.

Technical misalignment between optimization and control layers can create operational vulnerabilities. Qin and Badgwell [50] revealed how unrealistic setpoints generated by optimizers often trigger control system instability or safety interventions. These findings underscore the need for tighter integration between optimization algorithms and physical process constraints [44]. Effective optimization frameworks must balance computational precision with human expertise. Mayne [51] advocated for hybrid decision-support systems that augment rather than replace operator judgment. This approach preserves valuable operational experience while leveraging optimization capabilities, creating a collaborative environment for improved decision-making. Harjoto et al. [52] explore how corporate social irresponsibility, if unchecked can degrade portfolio performance and trust in optimization initiatives, particularly in cross-national contexts.

3.8 Emerging Trends and Future Directions

The optimization landscape is evolving through cyber-physical integration, edge computing, and sustainability-driven innovation. Autonomous operations are becoming reality through distributed sensor networks and edge-based optimization algorithms that enable remote assets to self-adjust with minimal human oversight. Energy systems are undergoing radical transformation as renewables integrate with conventional operations. Hybrid energy systems where intelligent algorithms dynamically balance grid power, solar generation, and energy storage to optimize both cost and carbon footprint which is an approach reducing emissions by up to 25% in field trials [6,53,54]. In the context of offshore renewables, Faria et al. [46] propose stochastic portfolio optimization models that integrate risk aversion and scenario generation, offering a viable pathway to blend oil and renewable portfolios under uncertainty. Reservoir optimization is advancing through digital core analysis and machine learning-enhanced EOR modeling. These technologies enable real-time updating of reservoir models, dramatically improving production forecasting accuracy for complex formations like tight oil and fractured carbonates [8,55]. Sustainability metrics are reshaping optimization objectives. Modern frameworks now incorporate carbon intensity, methane leakage, and water usage alongside traditional economic indicators. This multidimensional optimization reflects the industry's growing commitment to environmental stewardship and social responsibility [1], as described in Table 1.

Table 1. Summary of optimization techniques and their key attributes.

Technique	Application Area	Advantage	Limitation
PID Controllers	Well control, gas lift	Simplicity, reliability	Not adaptive
ANNs	Artificial lift, forecasting	Nonlinear modeling, real-time learning	Data dependence
Digital Twins	Offshore production, maintenance	Predictive, simulation-based insights	High implementation cost
MINLP Models	Production allocation	Multi-constraint handling	Computationally intensive
Edge Computing + IoT	Remote sites, real-time control	Fast, low-latency optimization	Network infrastructure dependency

Note: Table created by the authors based on insights synthesized from the reviewed literature.

Recent global trends in oil and gas optimization reveal a concerted shift toward integrated digital operations, emissions reduction, and cost-effective automation. Industry leaders are increasingly investing in platforms that connect real-time data acquisition, AI-driven decision engines, and advanced reservoir simulations, as seen in several flagship projects across North America, the Middle East, and Sub-Saharan Africa. For example, McKinsey & Company reported that over 70% of large oil and gas operators now allocate substantial portions of capital expenditure to digital optimization tools. In its Global Energy Perspective, McKinsey outlined how integrated planning frameworks combining drilling schedules, logistics, and market forecasts can lead to 15-25% increases in production efficiency when backed by intelligent automation systems [56].

In the United Arab Emirates, ADNOC (Abu Dhabi National Oil Company) has implemented a digital command center that aggregates data from more than 120 oilfields. Using digital twin technologies and predictive maintenance algorithms, ADNOC reported an 18% reduction in unplanned downtime and a 20% improvement in energy intensity metrics over three years [57]. This case demonstrates the operational and environmental benefits that arise from advanced optimization frameworks. Similarly, BP's Statistical Review highlighted that its deployment of AI-assisted production optimization at its Trinidad & Tobago gas operations led to increased output by 6% while reducing carbon intensity per barrel [2]. These gains were attributed to neural network models that processed real-time reservoir pressure and flow data to adjust compressor behavior and gas lift allocation dynamically.

In the Nigerian onshore sector, pilot projects initiated under the Nigerian Gas Expansion Program (NGEP) have emphasized gas flaring optimization. Modular flare gas capture units, coupled with remote sensing data and economic modeling, were deployed in the Niger Delta to evaluate reinjection versus LNG conversion options. However, comparative cost-benefit frameworks are increasingly shaping the way optimization strategies are prioritized under constrained resource settings [58]. While high-tech deployments dominate advanced economies, many operators in developing countries are adopting low-cost digital retrofits. In South Africa, optimization gains were achieved through better data governance and basic SCADA upgrades without major infrastructural overhauls [10]. These findings underscore that optimization is scalable and adaptable depending on maturity level, resource availability, and operational context. The global trend, therefore, supports a heterogeneous but converging movement toward smarter, greener, and more integrated oilfield operations. Industry case studies reinforce the assertion that optimization is not a luxury reserved for supermajors but a scalable necessity applicable across geographies and technological baselines.

4. Discussion

The analysis of optimization strategies in the oil and gas industry reveals a paradigm shift from isolated control systems to integrated, intelligent frameworks capable of responding to real-time field complexities. This transformation is characterized by the convergence of automation, artificial intelligence, and digital infrastructure across various operational stages from drilling and production to maintenance and energy efficiency management. One of the dominant trends observed in the reviewed literature is the growing application of ANNs and other machine learning techniques in optimizing artificial lift systems and well performance. Onomuakpose et al. [23] provided compelling evidence that ANN models trained with historical production data can predict optimal gas lift rates, wellhead pressures, and production volumes with high accuracy, even in the presence of noisy or incomplete data. This robustness underscores the potential of ML models to augment or even replace traditional rule-based control mechanisms in complex reservoir environments.

Complementing this approach, Ahmed et al. [59] confirmed the effectiveness of ML models in real-time optimization scenarios where data integrity may be compromised. Their findings align with the need for adaptive control systems that can dynamically adjust to fluctuating conditions, a feature increasingly demanded in offshore and marginal field operations. The integration of ANN models into decision-making frameworks also has direct implications for production allocation and reservoir management. Kosmidis et al. [35] and Beckner and Davidson [29] emphasized the utility of nonlinear programming and mixed-integer optimization for handling flow constraints, gas lift distribution, and facility limitations. These advanced algorithms provide the computational backbone for maximizing net present value (NPV) under constrained conditions. However, their practical implementation often suffers from computational intensity, prompting alternative strategies such as the multi-objective approaches proposed by Ray and Sarker [41], which ensure operational robustness without sacrificing optimization quality.

Beyond individual production units, the industry is also witnessing a digital transformation geared toward sustainability and energy efficiency. Shinkevich et al. [6] demonstrated that investments in digitalization particularly in IoT and cloud computing correlate strongly with reduced energy consumption and increased operational efficiency. By incorporating Cobb-Douglas regression analysis, they established that digital resource allocation is an optimization factor in its own right, significantly influencing output in the petroleum sector. This digital shift is not merely technical but structural. Munyai [10] emphasized the importance of data governance and lifecycle integration in enabling the success of optimization initiatives. In his analysis of energy operations in South Africa, he revealed that fragmented or siloed data systems severely limit the impact of digital tools, regardless of their sophistication. Therefore, optimization must be understood not only as a technological endeavor but also as an organizational imperative requiring alignment between data systems, workflows, and workforce capabilities.

Optimization also intersects with sustainability goals, especially in the management of APG. Rather than flaring, several studies advocate for conversion to LNG or reinjection into the reservoir. Ren et al. [28] showed that digital integration can aid in capturing, processing, and utilizing APG more efficiently, minimizing greenhouse gas emissions and improving profitability. These findings are echoed by McCarthy [33], who highlighted the benefits of intelligent automation and closed-loop systems in resource conservation. Digital twins and predictive analytics further exemplify how optimization strategies are extending into production forecasting and maintenance planning. Dmitrievsky et al. [49] illustrated the utility of digital twins in offshore platforms, enabling dynamic simulations of reservoir and equipment conditions, which in turn facilitate predictive interventions and minimize downtime. These technologies are proving critical in harsh environments where conventional monitoring systems are limited. Collectively, these contributions illustrate that optimization in the oil and gas industry has evolved from a reactive, siloed discipline into a proactive, integrative strategy underpinned by AI, digital infrastructure, and sustainable engineering practices. However, achieving the full potential of these advancements will depend on addressing current barriers such as data quality inconsistencies, skill gaps, and organizational resistance to automation.

5. Conclusion

Optimization in the oil and gas industry has evolved from marginal efficiency improvements into a comprehensive, multi-layered approach that integrates automation, advanced analytics, and digital technologies across upstream, midstream, and downstream operations. Feedback control systems, once limited to basic regulatory tasks, have matured into dynamic platforms capable of real-time modulation and self-correction under variable field conditions. Artificial intelligence (AI), and in particular ANNs, have introduced powerful modeling capabilities that enable the prediction and control of complex nonlinear behaviors typical of reservoir and production systems. These tools provide unmatched flexibility in handling noisy or incomplete datasets, enabling predictive maintenance, optimized gas lift allocation, and improved recovery strategies systems offer flexibility in managing noisy or incomplete datasets, supporting predictive maintenance, gas lift optimization, and enhanced recovery strategies. However, realizing these benefits depends on access to high-quality real-time data, seamless integration of surface and subsurface operations, and operator confidence in AI-driven insights. Increasing environmental responsibilities have elevated optimization to a strategic imperative, with technologies such as digital twins, edge computing, and predictive analytics enabling closed-loop systems that reduce emissions and improve gas utilization. This convergence of economic and environmental priorities signals a redefinition of optimization in the modern energy context.

Despite these advances, structural barriers persist. Organizational inertia, skill shortages, and fragmented data governance often limit the scalability and consistency of optimization efforts. Many enterprises continue to operate with disconnected systems and insufficient cross-disciplinary collaboration, undermining long-term gains. Addressing these challenges requires not only adopting new technologies but institutionalizing them through coordinated change management, workforce reskilling, and inclusive system design that aligns human expertise with machine intelligence. More so, the future of optimization lies in creating adaptive, data-driven ecosystems where operational intelligence is embedded across the asset lifecycle. Lasting impact will come from integrated frameworks that harmonize real-time control, AI, sustainability, and corporate governance. As digital infrastructure matures and external expectations grow, optimization will become a foundational element of responsible and resilient energy production.

6. Future Prospects and Way Forward

The future of optimization in the oil and gas sector will be shaped by three interconnected trajectories: the rise of hybrid AI systems, deep system integration, and alignment with sustainability imperatives. The new generation of hybrid AI combines the strengths of multiple paradigms such as rule-based logic, statistical modeling, physics-informed algorithms, and machine learning into unified frameworks capable of delivering higher accuracy, adaptability, and interpretability. These systems are poised to transform industry operations by enabling predictive and prescriptive decision-making across complex and multi-variable environments. For example, hybrid AI can integrate first principles reservoir models with real-time production data and reinforcement learning to optimize drilling parameters, enhance recovery strategies, and dynamically adjust to evolving subsurface conditions. Their successful deployment will depend on robust cybersecurity architectures, ethical AI governance, and transparent accountability frameworks to ensure operational trustworthiness.

System integration across organizational and technological domains will remain equally vital. Unified digital platforms that merge reservoir simulations, facility operations models, supply chain logistics, and environmental monitoring data into cohesive and interoperable ecosystems can significantly enhance responsiveness and situational awareness. Achieving this requires institutionalizing cross-functional collaboration among geoscientists, data scientists, control engineers, and sustainability officers, ensuring that hybrid AI solutions can seamlessly exchange information and adapt to new inputs without loss of performance continuity. Sustainability alignment will represent the most urgent and transformative priority. Future optimization strategies must align with global climate goals by embedding environmental performance targets such as Scope 1 and 2 emissions reduction, methane abatement, carbon capture and storage (CCS), and water use efficiency directly into AI-driven decision-making algorithms. Hybrid AI, with its capacity to reconcile economic objectives like NPV with environmental and social impact metrics, offers a pathway to achieving this balance. Governments and regulatory agencies should incentivize innovation by funding pilot projects that integrate hybrid AI into low-carbon oil and gas operations, while fostering partnerships between industry, academia, and technology developers to accelerate knowledge transfer and field deployment.

Education and workforce development will also be critical. Training programs must equip the next generation of engineers, data analysts, and decision makers with skills in hybrid AI design, data-centric engineering, and integrated asset management. This approach moves beyond digitizing existing workflows to reimagining optimization as a core driver of resilience, efficiency, and sustainability. Operators who embed hybrid AI into their technological, governance, and cultural frameworks will be best positioned to lead in the twenty first century energy transition, turning complex operational challenges into opportunities for innovation and competitive advantage.

Generative AI statement

The authors declare that no Gen AI was used in the creation of this manuscript.

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