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Leveraging AI for Intelligent Oilfield Development: A Pathway to Digital Transformation

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Graphical Abstract

Abstract

Artificial intelligence (AI) technology in the oil and gas sector is set to tackle significant issues, including environmental sensitivity and intricate production procedures. Recent breakthroughs in artificial intelligence have enabled the digital transformation and intelligent enhancement of petroleum firms. This article examines the developmental patterns of AI technology, emphasizing its applicability in the oil and gas industry. We evaluate AI technology implementation in domestic and foreign petroleum technology service organizations by evaluating industry features and business circumstances. The principal application domains of AI in the oil and gas sector are: dynamic reservoir analysis, sophisticated history matching, numerical simulation proxy modeling, and optimization of production plans. We underscore the need to dive into the issues encountered in developing oil and gas reservoirs by promoting advances in data standards, intelligent oil field management, and collaborative platforms. The "three modernizations" are essential for sophisticated study and management of reservoirs, enabling the rapid formulation of focused development plans. The article examines the future possibilities of AI technology, emphasizing the growing need for AI in developing digital oil fields in China. The results provide critical insights for the continuous digital transformation of oil and gas sector, highlighting AI substantial impact on improving operational efficiency and sustainability.

Keywords: *Artificial Intelligence, Oil and Gas Development, AI Algorithms, Oilfield Production Prediction, Enhanced Oil Recovery (EOR).*

1. Introduction

The rapidly developing discipline of artificial intelligence (AI) 1,2 in computer science aims to mimic, improve, and supplement human intellect.3-5 Recent research by Li et al.6 has explored the application of AI in the development of oil and gas reserves. According to Yao et al.7, the vast amount of data generated by oil and gas development, along with improvements in computing power and algorithmic breakthroughs, has dramatically sped up the progress of AI, making it a crucial part of Industry 4.0 and the current technological revolution.8 Kuang et al.9 have seen the growing significance of AI in the oil and gas industry's strategic energy initiatives. However, factors such as energy composition, geopolitical factors, pandemic repercussions, and dual carbon strategies have led to a deficit in China's oil and gas output,10 which needs to be improved to meet the country's increasing consumption needs. This has resulted in a significant reliance on foreign sources and heightened concerns about energy security.

The dual carbon strategy and the rapid rise of renewable energy sources provide significant challenges to the oil and gas sector, necessitating immediate reform and enhancement.11 The rapid progression of emerging technologies, especially artificial intelligence, has generated a fresh impetus for transforming and rejuvenating conventional industries in the digital economy. Shi et al.12 assert that the oil and gas sector is augmenting and revolutionizing its operations via digitization. The digital and cloud age enhances application value by integrating these technologies into the oil and gas industry.13 This reciprocal interaction between conventional industries and newer technology promotes ongoing innovation, generating novel situations, perspectives, and values owing to the vast industrial chain of the oil and gas industry.14-16

This article examines AI technology's present condition and developmental trajectories in oil and gas reservoir development. The report looks at the latest developments in AI and considerable data research in this field, assesses how local and foreign oil and gas companies build intelligent oil fields, delves into existing problems, and then suggests ways to solve them. This will be crucial for China's digital oil fields to grow.

2. Current Utilization of Artificial Intelligence in the Oil and Gas Sector

In the field of oil and gas exploration and production, artificial intelligence can analyse vast geological, geochemical, and geophysical data. Zhang et al.17 used multivariate time series and vector autoregressive models in machine learning to assist petroleum engineers in precisely identifying probable oil and gas reserves. Machine learning algorithms may discern hidden patterns in existing data via analysis and learning,18 therefore improving the accuracy and efficiency of research.

Figure 1 depicts the use of artificial intelligence across the whole oil and gas production process. Artificial intelligence technology facilitates intelligent manufacturing oversight and enhancement. By analyzing real-time monitoring data from production wells, we can swiftly detect abnormalities, predict oil and gas output, and execute suitable preventative measures to improve production efficiency and save costs. The analysis and processing of big data in oil and gas production provide more accurate prediction results to assist decision-makers in formulating logical plans. This will improve the management and decision-making processes in the oil and gas industry.

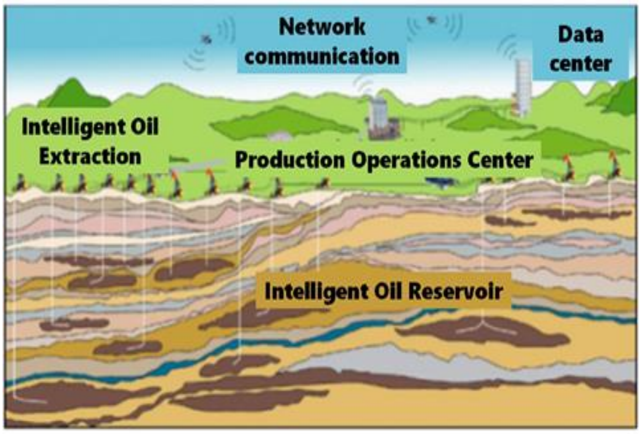

Figure 1. Graphical representation of artificial intelligence in oil and gas sectors.

Balashov et al.19 can develop suitable emergency response and rescue strategies for artificial intelligence via the analysis and learning from disaster scenarios. Statoil in Norway uses artificial intelligence technology for security monitoring and incident prevention in its offshore oil and gas operations, substantially reducing the likelihood of accidents. Shell, a prominent oil firm, uses artificial intelligence technology to proficiently oversee and optimise the administration of its refining equipment, markedly improving energy efficiency and product quality.20,21

The techniques used in oil and gas extraction mostly consist of advanced bottom-hole apparatus and sophisticated water injection technology. Advanced downhole equipment enables intelligent management of oil wells and improves oil recovery via adaptive control. Advanced water injection technology assesses and predicts underground aquifers. The water injection technique now includes astute changes that improve its efficacy. Artificial intelligence technologies in the oil and gas pipeline business principally include pipeline safety monitoring and advanced maintenance.22 Ongoing monitoring and assessment of pipeline data provide comprehensive supervision of operational conditions, allowing swift detection of problems and execution of necessary measures to ensure safe pipeline functioning. Intelligent maintenance technology enables sophisticated equipment management and utilises machine learning in the oil and gas industry by analysing data and forecasting pipeline equipment performance, hence improving equipment durability and operational efficiency.

The integration of artificial intelligence (AI) in fracturing technology marks a significant advancement in the oil and gas industry. This innovative approach involves the use of a permanent optical cable clamp attached externally to the casing string and the incorporation of an AI-driven fracturing sleeve within the casing string during cementing operations. As illustrated in Figure 2, the installation of AI fracturing system aims to enhance our understanding of oil and gas reservoirs and establish a foundation for future individual well fracturing, aligning with the reservoir's development history.23 AI fracturing sliding sleeves offer a distinct advantage over traditional completion methods by eliminating the need for ball-throwing or setting composite bridge plugs to isolate segments. Instead, AI-driven downhole tools activate the fracturing sleeve, thereby reducing interval conversion time and fluid volume. This technology also provides a unique emergency response capability. If necessary, the completion string can be equipped with the sliding sleeve and optical cable for deployment into the well, achieving full bore without subsequent drilling and milling operations. This reduces overall completion time and accelerates production. Operators favor this method due to its targeted modification capabilities, high operational efficiency, potential for liquid volume savings, and the ability to dynamically adjust fracturing designs using fiber optic data. The AI fracturing sliding sleeves are compatible with optical fiber systems, offering builders more flexibility in fracturing operations and giving operators enhanced control over the process. The implementation of multi-cluster fracturing techniques, such as bridge plug perforation fracturing, in heterogeneous reservoirs is associated with significant costs. Identifying the optical cable and adjusting the perforating gun's direction are critical steps to avoid cable penetration. Conversely, using AI fracturing sleeve structure with an optical cable anti-pinch damage function reduces operational risks and costs. Fracturing operations with a single inlet point can improve fluid flow rates, facilitate a quicker increase in sand ratio, and decrease the required hydraulic horsepower. This single injection point approach ensures the creation of a fracture in each channel, preventing the presence of unmodifiable areas.

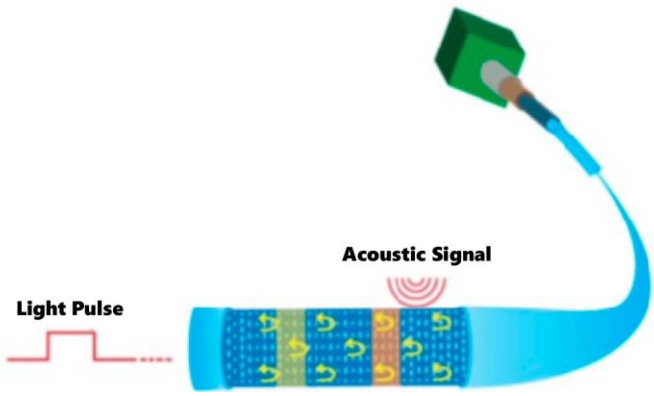

Figure 2. Schematic representation of artificial intelligence-induced optical fiber fracture.

Historically, decisions regarding the development of oil and gas reservoirs, both domestically and internationally, have relied heavily on empirical reservoir engineering methods.24 These traditional approaches often depended on outdated data and the personal experience of engineers, which are increasingly misaligned with the demands of modern reservoir development. Today, the advantages of artificial intelligence (AI) technology are becoming increasingly evident in various aspects of reservoir management. AI excels in dynamic analysis of oil and gas reservoirs, providing real-time insights that surpass the capabilities of conventional methods. Intelligent historical fitting allows for more accurate modeling of reservoir behavior over time, while numerical simulation proxy models offer sophisticated predictions of reservoir performance under different scenarios. Moreover, AI-driven production plan optimization ensures that extraction processes are not only efficient but also adaptive to changing conditions. These advancements collectively represent a significant leap forward, aligning reservoir development practices with contemporary technological standards and enhancing the precision and productivity of the industry.

In recent years, leading domestic oil companies such as PetroChina, Sinopec, and CNOOC have prioritized digital transformation as a key strategic direction. The integration of emerging technologies, including artificial intelligence (AI) and big data, with traditional oil and gas operations is accelerating. However, when compared to major international oil companies, several challenges remain. Multinational corporations still dominate the market for high-end programmable logic controllers (PLCs) and distributed control systems (DCS) at the data acquisition layer. Consequently, the digitization and networking rates of equipment need significant improvement. On the infrastructure front, China boasts world-class cloud computing capabilities, and Chinese oil companies have established private cloud data centers. At the platform service level, these companies have developed specialized oil and gas service platforms capable of providing microservices. Despite these advancements, there is a notable gap in the accumulation of experience and knowledge related to industrial mechanisms, processes, and modeling methods. At the application service layer, there is a shortage of mature professional software for exploration and development, and the industrial application developer community is underdeveloped. Addressing these gaps is crucial for enhancing the overall efficiency and effectiveness of digital transformation in the oil and gas sector.

China National Petroleum Corporation (CNPC) has significantly advanced the application of cutting-edge information technologies, including artificial intelligence (AI), within the exploration and development sector. The company has established a specialized research and development center focused on AI technologies for exploration and development, and has developed a cognitive computing platform tailored for these activities. This platform offers an integrated AI development environment that supports machine learning, data processing, model deployment, and inference applications by comprehensively considering data, simulation conditions, and algorithms. The implementation of this platform in practical business scenarios has notably reduced the research cycle for logging and identifying oil and gas reservoirs by approximately 70%, achieving an identification accuracy rate of over 90%. The "Exploration and Development Dream Cloud," recognized as the first fully controllable industrial Internet platform in China's oil and gas industry, has enabled PetroChina to construct the largest data lake in the Asian oil and gas sector. With the support of Dream Cloud, research and development efficiency in the Tarim Oilfield has increased by 30%.12 In an eastern oilfield, the use of AI for fault prediction in intricate fault block regions has decreased prediction time from 30 minutes to 10 minutes, resulting in a reduction in staff investment and effort by more than 40%. The efficiency of collecting activities has enhanced by 10% to 20%.

A Chinese research team employs machine learning to improve the investigation of oil and gas resources. They employ diverse intelligence algorithms to perform model training, automated feature engineering, and parameter optimization, enabling them to autonomously select the most suitable data model. This method enables sophisticated analytical scenarios, including the assessment of production capacity control variables, thorough sweet spot forecasting, and the optimization of fracturing parameters. The team incorporates deep learning techniques to create sophisticated models. This encompasses a reservoir uncertainty reduction model utilizing the Bayesian evidence learning framework; a sophisticated well-controlled reservoir state prediction and production analysis model employing convolutional neural networks (CNN); and a multi-sequence reservoir state analysis and production prediction model that integrates CNN and recurrent neural networks (RNN) across diverse geological conditions. They also develop a proxy model to optimize production control. These advances provide expedited design, real-time monitoring, efficacy assessment, prompt forecasting, and optimization of multi-well oil and gas field output throughout drilling and completion activities. This method also supports engineering solutions for reservoirs and lets reservoir models be improved and changed automatically using a lot of geological and engineering data.

3. The Advancement of Artificial Intelligence: Exploring New Frontiers.

3.1. Advanced Computational Methods for Enhancing Numerical Simulations Through Artificial Intelligence.

Artificial intelligence (AI) models for oil and gas reservoirs mimic fluid dynamics in subterranean porous media under diverse situations. By analyzing past reservoir data, these models can forecast oil well output, enhance water injection methodologies, and elucidate well interconnectivity.25 As the precision requirements for numerical models in oil and gas development increase, the processing time for simulations presents a significant challenge for automated history matching solutions. Agent models based on machine learning may rapidly provide simulation outcomes for reservoir models,26 markedly decreasing the computing expense of each simulation. Recently, artificial intelligence has used artificial neural networks to develop intelligent agent models for reservoir simulation history matching, sensitivity analysis, and uncertainty assessment. Historical reservoir data has effectively utilized these models, accurately predicting the output of the well. On top of that, these models have been successful in predicting the distribution of reservoir pressure and phase saturation both before and after injection in CO2-enhanced oil recovery reservoirs, which allows for faster predictions.

Artificial intelligence (AI) has significantly advanced reservoir modeling, particularly through the development of convolutional recursive hybrid deep learning proxy models. These models are highly efficient for automated reservoir history matching and uncertainty quantification.27 This study utilizes an image-to-sequence proxy modeling framework that integrates residual convolutional networks with multilayer recurrent neural networks to create a high-precision proxy model for reservoir numerical simulations, thereby enhancing both accuracy and efficiency. Automated history matching utilizes a multimodal distributed estimation approach to address the issue of multiple solutions. Principal Component Analysis (PCA) is used to reduce the dimensionality of extensive decision variables, facilitating the development of the proxy model.

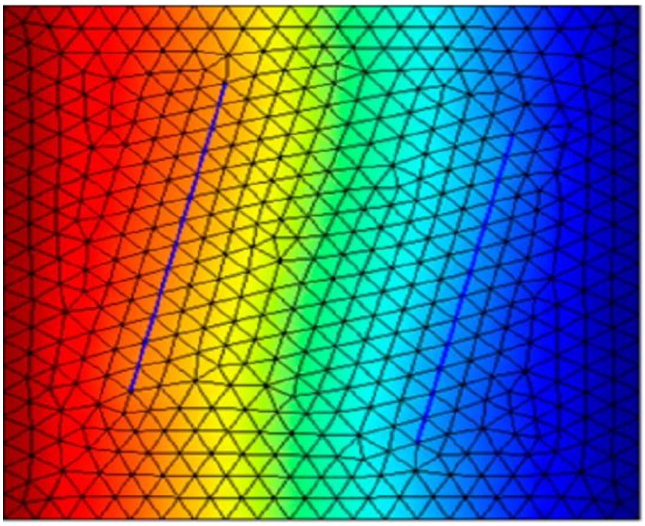

Figure 3. Digital Simulation Technology Powered by Artificial Intelligence.

Furthermore, Figure 3 illustrates a multiobjective evolutionary approach that uses approximation functions instead of conventional numerical simulations to optimize production plans. Deep neural networks are employed to develop the proxy model, which enhances geological model parameters using PCA, singular value decomposition (SVD), and tensor techniques. The Ensemble Smoother with Multiple Data Assimilation (ESMDA) is used for history matching. Results indicate that the proxy model significantly reduces the time required for numerical simulations compared to traditional approaches, thereby expediting the history matching process. A proxy model using radial basis functions is developed for multiobjective optimization in history matching. Five additive techniques for history matching, based on Pareto optimality criteria, are presented. Studies demonstrate that proxy model algorithms provide superior fitting accuracy and reduced computational costs compared to conventional techniques. An application scenario for an oilfield production optimization agent model, utilizing the Design of Experiments (DOE) method, is proposed. By testing several development plans within a designated block and analyzing their cumulative oil production and financial net present value, the pertinent parameters are determined as dependent variables. By adjusting constraint parameters, this method prioritizes experimental designs, demonstrating that proxy model algorithms can significantly enhance oilfield productivity.

3.2. Automated Recognition Technology Using Artificial Intelligence.

Automated identification using artificial intelligence (AI) is essential for the advancement of oil and gas reserves. This technique is intrinsically high-dimensional, intricate, and labor-intensive.28 Conventional history matching is arduous and requires considerable knowledge from scholars. Yang et al.29 presented an extensive digital platform for oil and gas exploration and production, markedly improving the efficacy of AI recognition. A number of non-gradient approaches to history matching have recently gained popularity. These include Markov processes, random gradient approximation techniques, ensemble smoothers with multiple data assimilation (ESMDA),30 and ensemble Kalman filters (EnKF).31 Simultaneously, progress in machine learning and deep learning has yielded novel methodologies for AI recognition, presenting fresh insights and resolutions.32-39

Artificial intelligence utilizes the Ensemble Kalman Filter (EnKF) methodology to automate history matching by constructing reservoir models and determining the requisite parameters.40-42 When you combine the Ensemble Kalman Filter with data from production, you can invert reservoir parameters and improve simulations, which makes fitting much more accurate.43-46 This method alleviates the burden on reservoir engineers and optimizes the history-matching procedure. Notwithstanding these achievements, China's petroleum sector continues to face upstream development problems.47-50

AI-driven automatic recognition implements a data-centric strategy to tackle the inversion of broken reservoir networks. This method combines Principal Component Analysis (PCA) with Discrete Cosine Transform (DCT) to quickly get geological data from very different reservoirs. This makes it easier to solve problems with nonlinear intelligent history matching. AI automated fitting approach initiates by analysing fitting phenomena, distinguishing between dynamic and static inconsistencies, and using empirical data to progressively enhance the model until it achieves accuracy criteria. This decreases the quantity of reservoir simulations required and enhances the effectiveness and precision of history matching.

AI has devised a sensitivity analysis method for historical matching parameters using adjoint models. This method establishes the coefficient matrix of the adjoint model, calculates the sensitivity coefficients, and determines the sensitivity coefficient matrix of the objective function in relation to the control variables. This strategy enhances the efficacy of parameter sensitivity analysis relative to experimental design methodologies and traditional gradient simulators.

The data-driven history matching technique, using deep learning via Convolutional neural Networks (CNN) and principal Component Analysis (PCA), attains excellent precision for both established and novel wells. Furthermore, AI continuously refines static model parameters, such as permeability, using the Markov Chain Monte Carlo approach, ensuring that the reservoir numerical model accurately reflects real production dynamics. This diminishes fitting time and enhances the efficiency and precision of history matching, rendering the anticipated oilfield development performance more indicative of actual production results.

3.3. Dynamic Analysis Technology in Artificial Intelligence.

The dynamic study of oil and gas reservoirs is a difficult multivariate and nonlinear task. Conventional reservoir engineering techniques often lack precision in calculations. Recently, this field has widely used machine learning methodologies such as artificial neural networks (ANNs), advanced simulation technologies, and support vector machines (SVMs). Figure 4 depicts the ideal production distribution between injection and production wells with a streamline model. In contrast to traditional techniques, machine learning improves the resilience and autonomous learning capacities of models, addressing the varied needs of several oilfield production phases. Artificial intelligence (AI) employs neural network algorithms to assess surface and reservoir data, accurately forecasting the average oil flow rate of multi-branch wells. When compared to older methods, long short-term memory (LSTM) neural networks have greatly improved the accuracy of predicting oilfield output, showing better performance in both convergence and prediction precision. Artificial intelligence improves predictive accuracy by using the correlation attributes between stratum and oil well output.51 Through the use of deep learning for fluid parameter prediction, AI creates a mapping link between applied research and oil and gas production in the investigation of reservoir inter-well connectivity. By feeding it certain starting points, AI can make predictions about other wells' saturation pressure, formation volume coefficient, and gas compression coefficient, among other metrics.

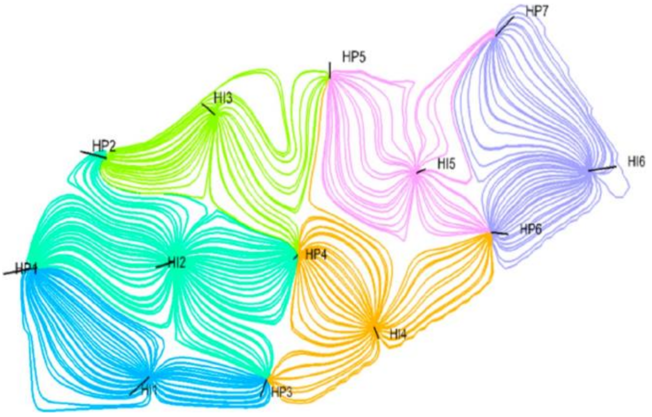

Figure 4. AI optimizes injection and production networks in oil and gas reservoirs using advanced simulations.

In accordance with the global trend in artificial intelligence (AI) advancement, AI has facilitated the optimization of fine water injection in mature oil fields by using big data.52 This sophisticated technique autonomously discerns the flow connections between stratified injection and production wells, enabling the computation of these correlations within designated blocks. Thus, it is possible to use multilayer and multidirectional production splitting technology to formulate effective water injection modification strategies. This method facilitates the computation of liquid and oil output from wells across various strata and orientations, hence improving the precision of production forecasts. AI utilizes multivariate time series (MTS) and vector autoregressive (VAR) machine learning algorithms to predict the output of water drive reservoirs. MTS analysis is used to optimize the data of injection-production well groups.53 A VAR model is then constructed to forecast production by using the interdependencies between the flow rates of injection and producing wells. Experimental findings indicate that machine learning models provide enhanced accuracy in yield forecasts and augment the dependability of the expected results. AI overcomes the constraints of conventional techniques for forecasting oil reserve output via water injection development. A new predictive model using artificial neural networks (ANNs) and a feature extraction technique that integrates fluid dynamics with measurement data has been developed. This approach assesses the model by computing the mean square error (MSE) and the coefficient of determination (R^2), producing error distribution histograms, and simulating data validation intersection plots. The methodology has shown encouraging experimental results, demonstrating significant improvements in predictive accuracy and model efficacy.

3.4. New AI Optimization Methods for Establishing Plans for Oil and Gas Reservoirs.

To accurately measure the amount of oil that is still in complex oil and gas reservoirs, we need to understand how the injection and production wells react to each other and figure out how to predict the connectivity links. However, due to inherent challenges in quantification, extended duration, and limited flexibility, current qualitative identification primarily relies on manual labor. Sophisticated optimization algorithms, such as particle swarm optimization and gradient-based techniques, can formulate optimal injection and production control strategies. Simultaneously, artificial intelligence (AI) utilizes advanced technologies, including neural networks and decision trees, to develop very precise geological and reservoir models. Through ongoing adjustments and refinements of these models, AI establishes a solid scientific basis for the creation and formulation of development strategies.

We have developed an AI-driven optimization technique for oil and gas reservoir development plans.54 This approach uses big data and artificial intelligence to forecast how well target reservoirs will produce, which improves recovery efficiency. This method allows for a more accurate characterization of the fluid distribution within the reservoir, streamlines the calibration of dynamic models, and enhances the quality of historical matching. Artificial intelligence utilizes convolutional neural network (CNN) technology for the automated analysis of well tests in radial composite reservoirs. This approach employs a logarithmic function for data transformation and utilizes mean square error (MSE) as the loss function. We can apply the derived optimal solution to interpret pressure recovery or pressure drop data from wells in radial composite reservoirs, enabling automatic initial fitting of well test parameters. AI currently facilitates swift dynamic predictions regarding oilfield development by utilizing digital reservoir analogy knowledge. This approach combines statistical analysis of similar reservoir samples, dynamic attribute simulation, and decline curve analysis. In fractured carbonate reservoirs, the expected outcomes include the amount of oil produced, the amount of water present, the length of the different stages of development, and the overall recovery rate. Furthermore, it establishes development performance indicators, including water-oil ratio and recovery degree, thereby validating the method's effectiveness and feasibility.

Based on a thorough research of artificial intelligence (AI) applications, system features including data integration, processing, and performance management have been developed. The virtualization and cloud-based sharing of diverse professional software have enabled online execution of development and research processes, while also improving company communication across numerous roles. The primary aim of AI application is to create an indicator system for assessing the efficacy of oil and gas field development. This entails using a fuzzy multiple assessment approach to evaluate reservoir development results and establishing a comprehensive sample library. The big data-driven methodology provides a fast and dependable decision-making framework for choosing growth plans from the sample library, thereby enhancing oil and gas field development strategies.

Artificial intelligence (AI) technology may use machine learning techniques to develop prediction models for individual well productivity in hydraulic fracturing. Probabilistic neural networks may maximize fracturing predictions for well sites, as seen in Figure 5. This model assesses the fracturing efficacy of each well and improves fracturing parameters by analyzing formation fracture pressure data, allowing precise forecasts of formation fracture pressure.

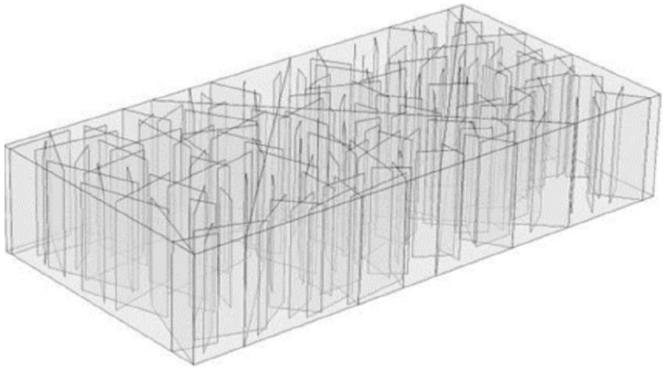

Figure 5. Technology that optimizes the placement of wells in oil and gas reservoirs using artificial intelligence.

AI furthermore suggests a methodology for developing dynamic response models for injection-production well clusters using neural networks. The link between injection and production wells could be explained by looking at historical production data and seeing how sensitive the connections are between the neural network model's output and input nodes. For example, AI combines horizontal well logging interpretation with seismic plane features to look at changes in lateral heterogeneity in order to solve problems like fast bottom water coning, high water content, and lower recovery rates in carbonate reservoirs. Using dynamic data to figure out inter-well connection gives a solid picture of how connected the reservoirs are, which helps with accurate evaluations and planning for growth. We use artificial neural networks to model injection-production interactions, creating an optimization framework based on Net Present Value (NPV) to enhance injection-production parameters. This method substantially mitigates problems associated with parameter tuning and historical fitting. The Dagang Oilfield No. 1 Oil Production Plant employs big data and deep learning techniques to forecast the potential of low-resistivity oil strata. This enhances the reference data available for finding prospective layers, improving algorithms, and implementing models. Through the quantification of the attributes of low-resistivity oil and gas reservoirs, AI revolutionizes the identification process from human expertise to intelligent analysis, thus enhancing predictive accuracy.

4. Future Trajectories in the Advancement of Artificial Intelligence Technology

The investigation and use of artificial intelligence (AI) in oil and gas reservoir development have yielded significant incremental outcomes. The intricate and dynamic subterranean conditions of these reservoirs, along with challenges like as data redundancy, absent features, and limited sample sizes, have exacerbated the difficulties of AI application. Furthermore, the research and production processes encounter substantial hurdles, such as considerable disparities in production capacity, intricate primary control elements influencing production, enormous workloads associated with classical numerical simulations, and protracted computation durations. Traditional solutions often fail to resolve these challenges efficiently.50-55 Artificial intelligence, with the amalgamation of machine learning and deep learning techniques, presents prospective answers to these intricate issues. In the future, artificial intelligence may be efficiently integrated with oil and gas field development to enhance reservoir management. Priority must be given to the "three modernizations": the standardization of oil and gas development data, the intelligence of oil and gas fields, and collaborative platforms.56 These advances will enable accelerated development and swift progress in AI applications within the oil and gas sector.57 Despite the prospects, AI technology continues to encounter both possibilities and obstacles. The main goal is to get the ideal solution for the intelligent development of oil and gas reservoirs. By concentrating on these modernizations, the sector may attain substantial enhancements in efficiency, precision, and overall performance.58,59

Figure 6 delineates the strategic framework for the progression of artificial intelligence (AI) technology in the oil and gas industry. The evolution of AI technology has experienced numerous stages, confronting a range of challenges as well as opportunities for growth and innovation. It may be possible to get a much better picture of oil and gas conditions by using smart applications in areas like dynamic reservoir analysis,60 advanced historical data fitting,61 numerical simulation models,62 and production strategy optimization.63 The main goal is to create more scientifically sound development strategies that enhance extraction rates and increase recovery efficiency. Future development plans for intelligent oil and gas fields will likely include AI-driven predictive analytics, real-time monitoring, and adaptive control systems to guarantee optimum performance. These developments will enable the extensive use of dependable and sophisticated growth tactics, eventually revolutionizing the sector. Moreover, the integration of AI with new technologies like the Internet of Things (IoT) and edge computing may significantly improve data collection and processing capabilities, resulting in more accurate and rapid decision-making. The ongoing enhancement of machine learning algorithms and deep learning models will be vital in tackling the intricacies of reservoir management and production optimization.64

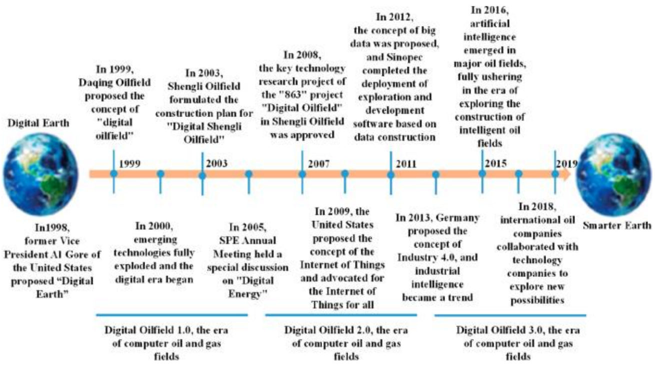

Figure 6. Strategic Pathways for the Future Evolution of AI in Oil and Gas Reservoir Management

The development of intelligent oil and gas fields is advancing swiftly, yet it is still in the preliminary phases of exploration. Notable obstacles remain, encompassing concerns regarding data integrity, the intricacies of algorithms, and the erratic characteristics of subsurface environments. Nonetheless, the future appears optimistic as developments in big data, artificial intelligence (AI), 5G, cloud computing, and the Internet of Things (IoT) propel the swift transformation of intelligent oil and gas fields. This progression represents a logical development in the evolution of oil and gas technology, serving as a calculated method for minimizing expenses, improving quality, and increasing efficiency in oilfield operations.65 The advancement of intelligent oil and gas fields requires a thorough integration of exploration and production activities with advanced technologies, including big data analytics, AI, cloud computing, and blockchain. This integration is anticipated to drive the development of transformative technologies in the oil and gas industry, meeting essential technical needs while improving economic and social outcomes.

To advance the development of intelligent oil and gas fields, it is crucial to prioritize data governance and the collection of extensive oil and gas reservoir parameter samples. These samples, influenced by geological, reservoir, and big data variables, will support a more comprehensive study of machine learning and deep learning methods. This approach will facilitate the transition from localized intelligent applications to extensive automation and intelligence, enabling more sophisticated analysis and management of reservoirs and the formulation of targeted reservoir strategies.

Principal Areas of Emphasis for Subsequent Advancement

1. **Enhancing AI Applications:** Integrating emerging technologies such as big data and AI is essential for achieving advancements in reservoir modeling, intelligent numerical simulation, dynamic analysis, optimization of development strategies, and impact assessment. Continuous innovation in methods and algorithms will enhance the intelligence level of oil and gas development, supporting the optimization of technological policies and the dynamic implementation of comprehensive adjustments.66
2. **Advancement of AI Collaboration Platforms:** The high costs and low efficiency of research and development in the oil sector impede the widespread use of AI. The current focus on robust AI development and the creation of extensive models as foundational infrastructure will facilitate the replication of applications on a broad scale. These models require less annotated data, provide superior performance, reduce labor input, lower marginal costs, and offer enhanced universality.67,68
3. **Advancing AI Innovation:** Oil companies should prioritize the use of domestically manufactured AI platforms, deep learning algorithm frameworks, and AI chips. Developing integrated software and hardware solutions specifically designed for oil and gas applications will enhance autonomous and manageable collaborative innovation capabilities. This strategy will promote the development of domestic AI products and solutions, driving progress in the sector.69
4. **Improving Cognitive AI Technologies:** Continuous advancements in cognitive intelligence technologies such as natural language processing (NLP) and knowledge graphs (KG) will facilitate the integration and development of multiple disciplines—from data to knowledge, understanding to reasoning, and perception to cognition. This will make operations in the oil and gas industry more logical, intelligent, and analytical.70
5. **Enhancing Digital Oil Fields:** Prioritizing the development of digital oil fields will enhance the intelligent management of oil and gas operations. This involves using AI and big data to develop digital twins of reservoirs, enabling real-time monitoring, predictive maintenance, and optimized production plans.71

It is essential to have enough high-quality training data available for artificial intelligence (AI) applications in the digital oilfield data domain. During the development of oil and gas reservoirs, a paradox frequently arises: an abundance of data exists, but there is a paucity of acceptable samples, especially a deficiency of "negative sample" data. Moreover, challenges such as inadequate data quality, insufficient standards, and restricted data sharing impede the entire realization of data value.72 Confronting these difficulties necessitates strong data governance and the use of extensive models to improve data value. The emergence of graphics processing units (GPUs) has considerably enhanced the training velocity of deep neural networks. However, the advancement of oil and gas reserves necessitates the need for high-performance computer capabilities. To address ultra-complex exploration and development difficulties, it is essential to consistently improve the complexity and generalization capacities of models. This entails the amalgamation of learning-based and model-based methodologies to develop more advanced and versatile AI solutions. AI technology has attained remarkable outcomes in the oil and gas sector; nonetheless, it still encounters considerable obstacles. Nonetheless, the future outlook for AI is optimistic. The oil and gas industry are prepared to completely adopt AI, which will promote sustainable growth across the sector. Utilizing AI enables the sector to attain greater resource efficiency, higher recovery rates, and enhanced efficiency in operation.73

5. Conclusion

1. **Improving Data Standardization:** It is essential to reinforce the standardization of artificial intelligence data. This involves implementing stringent data governance practices to enhance data quality, automate processes, and elevate the sophistication of data processing operations. Maintaining uniform and high-quality data is crucial for the efficacy of AI applications in the oil and gas sector.74
2. **Emphasizing AI Model Algorithms:** Petroleum companies should implement autonomous, controlled, and advanced AI modeling platforms. These platforms must facilitate data processing and feature engineering specifically tailored to the unique processes of oil and gas operations. Enhancing the generalization capability of AI models will result in more precise and dependable forecasts and optimizations, thereby improving operational efficiency.
3. **Enhancing Collaborative Platforms:** To stimulate innovation, petroleum companies must improve interdisciplinary cooperation. This involves enhancing collaborations with fields such as geology, geophysical exploration, and reservoir engineering. By addressing critical challenges together and thoroughly incorporating advanced information technologies like AI, these partnerships can drive substantial progress and resolve complex issues more efficiently.
4. **Establishing Intelligent Oil and Gas Fields:** Petroleum firms must prioritize the “three modernizations”: data standardization, oil and gas field intelligence, and platform collaboration. This strategy will facilitate leapfrog development and rapid progress in AI applications within the oil and gas sector. By emphasizing these advancements, the industry can achieve significant improvements in efficiency, quality, and overall performance.

Through the implementation of these strategies, the oil and gas sector can fully leverage AI, resulting in transformative progress and sustainable development. The integration of AI will not only address existing challenges but also enable innovative solutions that enhance operational efficiency, reduce costs, and increase overall productivity in the industry.75 The strategic use of artificial intelligence will propel the oil and gas industry towards a more intelligent and sustainable future.

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