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The Evolution of AI in the Oil and Gas Industry: From Digitization to Intelligent Decision-Making

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Abstract: Artificial intelligence and deep learning are becoming increasingly important in oil and gas field development, gradually becoming the development trend and research hotspot in the petroleum industry. Currently, over 70% of large oil and gas enterprises worldwide have listed the "physical-data dual-driven" model as their core strategy to make up for the shortcomings of pure data-driven models in generalization with small samples. This article focuses on the combination of the three major algorithms (CNN, RNN, and RL) with oil and gas development, reviews related research at home and abroad, and presents the main implementation methods of related core technologies as well as the problems they face. Focusing on the three mainstream machine learning algorithms, it explores the technical paths and key issues for the upgrade of the entire chain of perception, prediction, and decision-making in the oil and gas industry based on the data-driven paradigm, providing a reference for the intelligent transformation of the oil and gas industry.

Keywords: Artificial intelligence; Deep learning; Oil and gas development; Data-driven model

The rapid development of artificial intelligence (AI), machine learning (ML), and deep learning (DL) has brought about transformative changes that have enhanced labor productivity, reduced labor costs, optimized human resource allocation, and generated new job demands [1]. The significant role of the oil and gas industry is well-known, which has subsequently led to a series of studies exploring the challenges and opportunities in its application process [2]. The latest oil and gas industry survey reveals that over 70% of large oil and gas companies have adopted the "physical-data dual-driven" model as an important strategy to address the limitations of pure data-driven models in generalizing from small samples [3].

AI simulates the thinking process of humans and can automatically emerge patterns, generate predictions, and optimize decisions from numerous data, and has increasingly played a role in many fields such as healthcare, finance, and manufacturing. The core AI technologies represented by convolutional neural networks

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(CNN), recurrent neural networks (RNN), and reinforcement learning (RL) have far exceeded the performance of traditional intelligent methods in numerous issues such as image recognition, time series analysis, and autonomous decision-making, especially in complex seismic data processing and interpretation during the exploration stage, where deep learning has a very promising application prospect [4], and is an important tool for solving complex problems.

The oil and gas industry is an important pillar for maintaining global energy supply. The oil and gas industry extraction faces severe challenges. China's unconventional oil and gas development also faces two aspects of geological-economic "bottlenecks": one is that the mechanism of enrichment in sweet spots remains unclear in complex geological settings, resulting in inaccurate predicted scale reserves; the other is poor resource endowment (such as low EUR per well and low recovery rate), which determines the limited development benefits [5]. At the same time, the heterogeneous data (seismic, logging, real-time sensor data, production history) formed by oilfield development has been growing rapidly, but due to the lack of efficient data analysis and mining methods, the data value is low, and there are new contradictions such as "having data but being ignorant". To address these contradictions, the big data analysis platform based on cloud computing is developing towards the "lake-storage integration" goal, providing infrastructure for the real-time construction of heterogeneous data governance [6].

With the development of new-generation information technologies such as the sensor layer of the Internet of Things, edge computing nodes, and cloud-based big data platforms, the intelligent development of the entire life cycle of oil and gas reservoirs has become the development trend of international oil companies. Currently, large oil and gas fields in various countries have achieved large-scale application of 3D geological modeling, real-time network monitoring, and production data collection and analysis systems, and domestic and foreign large oil and gas fields have achieved full-factor upgrading of digital development. On this basis, digital twin technology has been (or is being tested for use in) various links of the oil and gas value chain, such as upstream (exploration and drilling), midstream (oil pipelines and transportation), and downstream (processing plants and refining) [7]. At the same time, it has achieved interaction between the physical reservoir and the virtual model, transforming static asset descriptions into dynamic closed-loop systems [8].

The industry is transforming from "digitally describing industry assets" (such as visualizing wellbore parameters) to "intelligent decision-making hubs", replacing the technical process of development decisions with deep learning and dynamically improved algorithms. The integration of AI and oilfield development is an inevitable direction of technological progress [9], and the data-driven models established by AI can significantly accelerate the speed of reservoir history fitting, improve real-time control of drilling routes, and achieve the prediction of equipment failures, dynamic adjustment of mining operation plans, etc. [10], solving the problems of insufficient effectiveness, ability, and flexibility of conventional technical means.

For example, Rao et al. [11] were the first to replace the MLP in the traditional PINN with the new generation KAN, thereby constructing the PI-KAN model. By using the mixed pressure-velocity formula, they successfully simulated the fluid flow in strongly heterogeneous porous media, and were able to better handle the leakage problems in heterogeneous reservoirs. In the identification of seismic faults, the advanced U-Net can automatically detect very fine faults [12]; In terms of capacity prediction, machine learning that takes physical constraints into account can significantly enhance the accuracy of steady-state capacity and transient production predictions [13], surpassing the limitations of existing methods in terms of capability, precision, and applicability. With the annual exponential growth of oilfield production data and the upgrade of computing machine hardware, it has become increasingly difficult for empirical models to handle the complex underground systems. This paper extensively collects the latest works from both domestic and international sources, and summarizes the data-driven modeling approach of machine learning (ML) for the overall upgrade of the perception, prediction and decision-making chain in the oil and gas industry. The article focuses on three major machine learning algorithms, and analyzes the methodological issues ranging from the algorithm overview and the adaptability to oil and gas problems simulation to the practical effectiveness and technological innovation of industrial cases.

1 Convolutional Neural Network

Tracing back to the mechanism of the biological visual cortex, the Convolutional Neural Network (CNN) is a deep learning architecture inspired by the mechanism of the biological visual cortex, integrating the characteristics of local connections and weight sharing. After efficiently extracting features through the convolutional layer, by leveraging the features extracted by the convolutional layer, and then compressing the dimensions through the pooling layer to obtain invariance to translation and deformation, it is finally handed over to the fully connected layer to complete the global mapping and decision-making [14]. By eliminating the complex parameters similar to those of traditional fully connected networks, the optimization threshold of CNN has significantly decreased. Especially when dealing with grid-like topological data such as three-dimensional seismic bodies, core CT scans, and logging array signals, it plays a greater role [15]. CNN preserves the spatial topological information intact, completely bypassing the complex extraction process of traditional manual feature engineering, and can play a greater role in the interpretation of oil and gas geological images.

1.1 Seismic Structural Interpretation and Fault Identification

In actual seismic interpretation work, the process of structural interpretation has undergone a qualitative change due to the popularity of CNN. The most typical example is the fault identification stage: multi-scale convolution kernels can intuitively capture the imprint of coherent axes misalignment and other stratigraphic discontinuities; in contrast, older-generation algorithms such as random forests always destroy the spatial continuity logic when dealing with such tasks [16]. If encountering complex structural areas, the signals of tiny faults are easily swallowed by background noise. At this time, it is necessary to make efforts in the network architecture. Wang et al. [17] had solution is to introduce a dual-path U-Net architecture. They not only embed the global attention of Transformer but also add attention gating at the interface of the encoder and decoder. This design achieves very good noise reduction effects. Even when analyzing samples with extremely poor signal-to-noise ratio, it can pull the F1 score of tiny faults up to above 0.85. In response to the practical problem of insufficient labeled samples, Gao et al. [18] started from the optimization of 3D convolution kernels and developed an end-to-end method for generating fault probability volumes. This method completely put aside manual feature intervention and demonstrated a very solid anti-interference foundation when running actual seismic data. Wu et al. [19] improved the U-Net architecture to address the problem of multi-scale feature fusion. He also implanted a function module containing dilated convolution between the encoder and decoder, expanding the receptive field and enhancing the network's ability to capture fine faults. In more complex fracture-cave reservoir identification, Gui et al. [20] improved U-Net++ network outperformed traditional coherent body attributes and standard FCN models in the accuracy of fault-carst form reservoir identification.

1.2 Salt Dome Exploration and Semantic Segmentation

The boundaries of salt domes are already blurry, and their geometric shapes are complex and variable. Traditional interpretation methods are difficult to apply in deep-water oil and gas exploration. Islam et al. [21] systematically summarized the salt body segmentation architecture based on deep learning, and the U-Net variant and generative adversarial networks were tested on benchmark datasets in a horizontal manner. It was found that the poor quality of data and the single evaluation indicators were the main problems currently preventing the industrial deployment of such models.

To overcome the limitation of insufficient generalization ability, Xu et al. [22] proposed a multi-task dense three-dimensional salt body prediction method based on unsupervised embedding. They solved the problem of large differences in data distribution across different regions by using the contrastive learning scheme, which enabled the recovery of more detailed three-dimensional salt body shapes. Kanumalli et al. [23] proposed a convolutional neural network based on edge constraints and feature fusion. This model introduced an explicit edge detection branch in the decoder stage and integrated deep semantic and shallow texture information through a multi-scale feature fusion module, solving the problem of "over-segmentation" or "under-segmentation" caused by blurred salt body edges, and achieving significantly higher edge positioning accuracy in actual seismic data than the standard U-Net. To address the issue of severe reliance on manual experience in seismic interpretation, Waldeland et al. [24] explored a texture feature classification method based on CNN, proving that even with limited labeled samples, three-dimensional CNN can depict the complex topological structure of salt mounds using local receptive fields. Ali et al. [25] developed a convolutional neural network combining rock physics-driven and transfer learning, using a pre-trained model based on synthetic data and transferring it to the actual site, enhancing the accuracy of salt subsurface layer elastic property prediction and lithology identification.

1.3 Well Logging Rock Type Recognition and Multi-source Fusion

In addition to image data, CNN has also made breakthroughs in rock type recognition of one-dimensional well logging data. Well logging curves have the characteristic of nonlinear mapping in the depth direction. Shi et al. [26] proposed an end-to-end recognition method based on a depth residual network (ResNet), using deep convolutional kernels to extract high-dimensional features of curves such as natural gamma and density, achieving the highest 88% classification accuracy in the task of complex carbonate rock and shale lithology prediction in the southern Sichuan Basin, significantly superior to traditional machine learning algorithms such as random forests. Rao et al. [27] proposed the discrete variable (DV) - circuit quantum - classical physics - informed neural network (QCPINN), and for the first time applied it to three typical reservoir flow models, verifying the feasibility of QCPINN in reservoir engineering applications.

Current research is shifting from relying solely on data to "geology + data" two-legged walking. The samples of unconventional reservoirs are highly unbalanced. Chen et al. [28] developed a framework that uses geological information to drive deep learning. He added a "stratigraphic sequence constraint" regularization term to the loss function, forcing the model to follow the up-down contact relationship of sedimentary strata, thus avoiding missing thin interlayers and rare lithologies, and raising the F1 score of rock type recognition to over 90%. During the review of old wells, a common problem is the lack of core data (small samples). Sun et al. [29] used meta-learning methods. They used model-agnostic meta-learning algorithms to enable neural networks to "learn how to quickly adapt to new tasks", and the model's generalization ability significantly improved in the absence of much well logging data. Rao et al. [30] proposed the Boundary Integral Neural Network (BINN), which transforms partial differential equations into boundary integral equations and combines deep learning to solve two-dimensional flow problems of anisotropic reservoirs by reducing dimensions. The latest research also indicates that a single model is difficult to simultaneously capture local features and long-term dependency relationships. Wang et al. [31] proposed a convolutional long short-term memory network, using CNN to extract local spatial fluctuation features of well logging curves, and LSTM to capture vertical sequence dependency in the depth direction. This method is more stable and accurate than using a single CNN or RNN model when recognizing complex lithology in complex strata.

2 Recurrent Neural Networks

Just having spatial features is not enough. The dynamic evolution of oil and gas development ultimately is a very difficult problem in time series. To transition from static seismic interpretation to dynamic production prediction, recurrent neural networks [32] need to analyze the deep mapping relationships in time series. As a powerful tool specifically for time series data, RNN's role is to use recurrent hidden states to relay and pass historical information, enabling the algorithm to generate dynamic memory. Later, LSTM (Long Short-Term Memory unit) and GRU (Gated Recurrent Unit) were introduced with gating mechanisms in their structures, solving the problem of gradient disappearance and making the grasp of long-term dependency relationships much more accurate. Compared with traditional time series models like ARIMA, RNN has a much stronger ability to capture nonlinear change patterns. Therefore, for tasks such as speech recognition, natural language processing, and early warning of equipment degradation and monitoring of oil and gas production, the modeling of dynamic systems now almost always uses it.

2.1 Dynamic Production Forecasting and Hybrid Optimization Model

To address the limitations of a single LSTM model in processing long-term production data, which can easily fall into local optima, He et al. [33] proposed a hybrid prediction model based on simulated annealing algorithm to optimize LSTM. Through a global optimization algorithm, it automatically adjusts the hyperparameters (such as time step, number of hidden layer nodes) of LSTM. This model shows very high stability in daily production prediction of tight oil reservoirs, with an average absolute percentage error of only 4.12%. Recurrent Neural Network (RNN) models through the modeling of gated temporal units (LSTM/GRU) for long-term memory dependencies solve the failure of traditional statistical models (such as ARIMA) in handling nonlinear trends. The processes of oilfield decline in production, equipment degradation, etc. all have this effect, that is, the current bottom hole pressure is affected by the injection history one month ago [34]. Rao [35] was the first to introduce the variational quantum algorithm (VQLS) into streamline reservoir simulation. They used quantum computing to solve the pressure equation and combined it with the high-order WENO scheme to calculate the water saturation along the streamline. Xu [36] used ARIMA to predict the linear part, and then used GRNN to compensate and combine the residuals, significantly improving the lag of ARIMA and the medium and long-term prediction error was 3.43%. Ge [37] constructed a double-layer LSTM model to achieve multi-variable, high-precision production prediction for complex water-driven oil reservoirs, realized the optimization scheme of injection parameters zoning, and the collaborative prediction of pressure field and dynamic production, with a determination coefficient R^2 >0.91 for the prediction results. Rao et al. [38] applied the improved variational quantum linear solver (VQLS) to the field of solid mechanics and successfully calculated the displacement distribution after finite element discretization under plane strain conditions. This method has significantly improved in terms of convergence and calculation accuracy compared to its predecessor. Martínez et al. [39] introduced a gene data-driven model based on recurrent neural networks to predict the time-stamped sequence of complete production rates (oil, gas, and water), and embedded the physical equations constraints of the wellbore pressure as the target variable, applicable to both actual and synthetic reservoirs.

2.2 Physical Constraints and Diagnosis of Complex Dynamic Systems

To make data-driven models easier to understand, the integration of physical knowledge neural networks and RNN has become a research hotspot. Li et al. [40] built an LSTM model with physical constraints to predict water injection development, adding the mass conservation equation to the loss function. This model not only can accurately predict the trend of water saturation but also ensures that the prediction results comply with the basic principles of reservoir engineering (such as cumulative production will not decrease), effectively avoiding “non-physical” prediction values. Jin et al. [41] developed a physical information encoder-decoder framework, with LSTM as the core component, embedding the physical equations constraints of fractured horizontal wells into the sequence-to-sequence learning process, successfully replacing the traditional, time-consuming numerical simulation, and strengthening the generalization ability of production sequence prediction from multiple aspects. In the field of carbon sequestration, Shokouhi et al. [42] integrated Darcy’s law and the mass conservation equation into deep learning, and used the physical-constrained model to make good predictions of the time and space evolution of the pressure field and water production rate after CO_2 injection. Rao et al. [43]

constructed a quantum neural network (QNN) based on the principles of quantum entanglement and superposition. They used parameterized quantum circuits to efficiently predict and classify the potential for CO_2 dissolution and storage in saline layers. In gas well management, Sinha et al. [44] proposed a time series detection model based on bidirectional GRU for early diagnosis of gas well liquid accumulation. This model can capture the subtle lag characteristics of changes in oil pressure and casing pressure, and can identify the risk of fluid accumulation 30 days earlier than the traditional critical flow rate model, thus providing valuable time for the implementation of drainage gas production measures. Amelia et al. [45] verified that the GRU module has a higher feature extraction efficiency than the traditional RNN when processing high-frequency crude oil price fluctuation data, providing more reliable input for economic evaluation.

3 Reinforcement Learning

Reinforcement learning is a machine learning method specifically designed to solve sequential decision-making problems [46]. Its focus is to enable the agent to learn without explicit external supervision, but through the "trial and error" method of continuous interaction with the environment. It learns by relying on the reward or punishment signals from the environment feedback in the Markov decision process, aiming to maximize cumulative rewards to learn the optimal strategy. The main technical innovations include Bellman equation-driven value iteration, temporal difference learning and policy gradient theorem, and in combination with deep networks (such as DQN, PPO algorithms), it successfully breaks through the "dimension disaster" limitation of traditional reinforcement learning in handling continuous high-dimensional state spaces [47]. Currently, the sequence decision framework based on deep reinforcement learning has demonstrated superior optimization ability over traditional control algorithms and has become the core technology support for the improvement of intelligent oil fields in complex geological conditions (such as water injection improvement, trajectory control) [48].

3.1 Reservoir Management and Multi-Agent Control

In the complex reservoir dynamic management of water injection and artificial lift, reinforcement learning shows greater potential than traditional control algorithms. Abdalla et al. proposed a new multi-agent physically-informed reinforcement learning method for water injection improvement. This method combines the advantages of reinforcement learning and physical-based modeling, not only reducing water consumption and related costs, but also maximizing economic benefits [49]. To further solve the generalization problem brought by geological uncertainties, Nasir et al. [50] established a constrained deep reinforcement learning framework for the development of underground two-phase flow. The results confirmed that the agent can work under the safety constraints of the bottom hole flow pressure and the upper limit of the injection water, and this type of learning framework significantly enhanced the net present value throughout the life cycle. Miftakhov et al. [51] pioneered the reinforcement learning model based on "pixel data". The developed model does not require input of complex rock physics parameters, but can output the optimal water injection policy by only relying on the dynamic grid pixel images of the pressure field and saturation field, providing a new paradigm for reservoir management without models. In the field of artificial lift optimization, Faria et al. [52] proposed a deep reinforcement learning method combining physical information neural networks. This method uses the fluid dynamics model of gas lift wells as an environment simulator, training the agent to automatically adjust the opening degree of the injection valve under different conditions. Experiments show that this method reduces 15% of injection costs compared to traditional PID control while maintaining stable production. Rao [53] systematically optimized the quantum circuit structure of the Ansatz in VQLS, significantly improving the convergence speed and calculation accuracy when solving the discretized reservoir flow equations. Ding et al. [54] proposed a personalized reinforcement learning method based on reservoir heterogeneity images. With only a single simulation, the personalized reinforcement learning method achieves real-time decision-making for new well production strategies through sample enhancement and pre-trained models, and the agreement of the optimal solution exceeds 95%. The SAC algorithm shows better performance in complex geological conditions and has significantly enhanced computing capacity compared to traditional methods.

3.2 Drilling Engineering Optimization and Perception-Decision Integration

In drilling engineering, the underground rock layer environment is invisible, which poses great challenges to the nonlinear and time-varying nature of parameter optimization. The traditional optimization of oil well control relies on numerical simulation combined with search algorithms (such as the improved particle swarm optimization). The problem lies in the large amounts of repetitive calculations and the fact that historical experience is difficult to apply [55]. Amadi et al. [56] proposed using reinforcement Q-learning for decision-making. Reinforcement Q-learning can be used as a decision-making tool for drilling operations, providing an engineering method to optimize the selection of operating parameters, and enhancing the drilling capacity in terms of cost and time. Nautiyal et al. [57] developed a ROP prediction model, using RandomizedSearchCV to develop the ROP prediction model, and using methods such as RandomizedSearchCV (for hyperparameter adjustment) to increase the accuracy of the model. They also used the evolutionary particle swarm optimization algorithm to maximize the ROP and listed a detailed parameter list for developing accurate and universal machine learning models, significantly enhancing the drilling capacity.

To meet the requirement of millisecond-level adjustment of mechanical drilling speed parameters, Huang et al. [58] developed an automatic drilling system based on the deterministic policy gradient (DDPG) strategy. This system designed a combined reward function that included drilling speed, mechanical specific energy (MSE), and vibration intensity, to dynamically adjust the drilling parameters of complex formations. Experiments proved that it could effectively suppress stick-slip vibrations and enhance the drilling capacity by 20%. Vishnumolakala et al. [59] confirmed that deep reinforcement learning has a high tolerance rate in geological guidance, and even if the initial geological model is biased, the agent can correct the wellbore trajectory based on real-time logging data. The research significantly increased the drilling rate of reservoirs. Liu et al. [60] introduced a closed-loop machine learning framework to perform real-time lithology identification and autonomous parameter improvement, compared with traditional offset drilling, the ROP of the test well increased by 17.4%, the non-productive time decreased by 37.8%, and the stuck pipe incidents decreased by

87.5%. An et al. [61] integrated the improved YOLO detection algorithm with reinforcement learning decision-making and applied it to the intelligent detection and path planning of pressure release holes in mines. This research demonstrated the potential of "perception-decision" integration in extreme environments for this field.

4 Conclusions and Future Prospects

(1) When relying solely on data-driven models to handle geological problems, the shortcomings become increasingly obvious. This includes too few samples, making CNN difficult to interpret complex structures; the underground data itself has limitations, and the dynamic predictions of RNN are mostly distorted. Reinforcement learning has been applied to the improvement of well groups, but the convergence has always been an industry challenge. The modeling approach should shift towards being dominated by geological priors, "knowledge-driven". In the execution architecture, the sedimentary laws should be directly written into the self-supervised pre-training framework, such as developing physical information neural networks (e.g., PINN-RL) that couple the seepage equations, adding physical regular terms such as mass conservation to the loss function, and using fluid mechanics and formation laws to hard constrain the algorithm. This physical and data-driven mechanism can maximize the suppression of non-physical prediction values and has more reliable generalization performance in the case of small sample conditions.

(2) In oil and gas development, there is a problem that has not been well solved - exploration interpretation, dynamic simulation, and end production operate independently. To change this situation, an intelligent decision-making system that can manage the entire process must be established. From a technical perspective, it is necessary to combine CNN's spatial resolution, RNN's temporal modeling, and reinforcement learning's decision-making ability. The foundation of this system is the high-fidelity virtual reservoir built by digital twin technology, which can transform fixed static assets into adjustable dynamic closed loops. During actual operation, GRU is responsible for real-time capture of changes in reservoir status, and the aforementioned PPO algorithm then provides detailed production intervention instructions. For this closed-loop from geological cognition to automatic execution to be truly put into use, it is currently mainly blocked at two points: one is the feature dimensionality reduction of the high-dimensional state space, and the other is how to handle the control robustness brought by geological uncertainty.

(3) Breakthroughs in underlying hardware such as computing power and communication are reshaping the entire production mode. Take reservoir numerical models as an example, once quantum computing can be truly utilized, the simulation time for trillions of grids can be shortened by several orders of magnitude, providing computational power guarantees for millisecond-level real-time control. 6G networks and millimeter-wave transmission also provide solutions to the communication bandwidth problem in deepwater oil fields. More importantly, the trend of full autonomy at the operation end is noticeable: with embedded reinforcement learning, intelligent drilling machine groups can complete complex trajectory planning through distributed algorithms. At the micro level, in conjunction with nano sensor arrays and graph neural networks, it is even possible to conduct real-time diagnosis of pore-level seepage. These cutting-edge technologies, when combined, are fundamentally

transforming the operation methods of the oil and gas industry.

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Author Contributions

All authors contributed to the study conception and design, data collection, analysis and interpretation of the results, and manuscript preparation, and take responsibility for the integrity of the work.

Availability of Data and Materials

None.

Conflicts of Interest

The authors declare that they have no conflicts of interest to report regarding the present study.

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