Application and Progress of Artificial Intelligence in Oilfield Drilling

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Abstract. Intelligent drilling and completion technology was an organic integration of drilling and completion engineering with advanced technologies such as artificial intelligence, big data, and cloud computing. It could achieve precise characterization, optimized decision-making, and closed-loop control of the oil and gas drilling and completion process. It was expected to significantly improve drilling and completion efficiency, reservoir drilling rate, and oil and gas recovery rate. It was a research frontier and hotspot in the field of oil and gas. This article constructed an artificial intelligence application scenario system for oil and gas drilling and completion based on engineering practice. It also elaborated on the current research status of intelligent drilling and completion theory and technology at home and abroad. Apart from that, the article summarized the challenges and key research directions faced by intelligent drilling and completion technology research. The aim was to provide a reference for accelerating basic theoretical research, technology promotion, and application of intelligent drilling and completion technology in China.

Keywords: intelligent prediction, parameter optimization, Mechanism Data Joint Drive.

1. Introduction

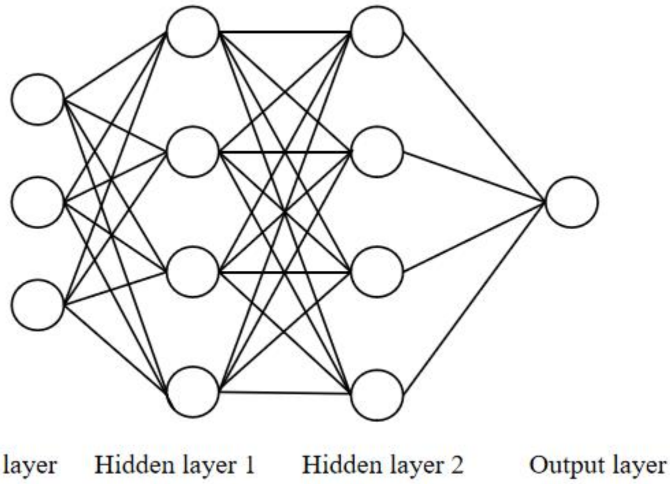
Artificial intelligence in oil and gas drilling and completion engineering was applied in integrating geological engineering data, intelligent algorithms, engineering theory, tool equipment, and system platforms in specific drilling and completion processes. It also involved adapting to technical requirements and responding accordingly. It had clear data requirements, application processes, technical goals, etc. It was an important foundation for the deep integration of artificial intelligence technology and oil and gas drilling and completion engineering. And it was the key to the implementation and application of intelligent technology.

Based on technical requirements and engineering processes, this article constructed an artificial intelligence application scenario system for oil and gas drilling and completion from different perspectives such as efficiency, quality, and safety. The application of artificial intelligence in oil and gas drilling and completion engineering included intelligent prediction, parameter optimization of mechanical drilling speed, closed-loop control of wellbore trajectory, and dynamic control of drilling risks. It also involved intelligent evaluation and optimization control of cementing quality, design and optimization control of fracturing schemes, completion plans, and production optimization.

2. Application

2.1 Intelligent prediction and parameter optimization of mechanical drilling speed

In the underground rock breaking environment, dynamic changes and interference factors posed challenges for engineers to meet accuracy and efficiency requirements. Predicting mechanical drilling speed and optimizing drilling parameters based on experience and traditional mechanism models became difficult in such conditions. So quickly and accurately improving the mechanical drilling speed, obtaining the main influencing factors, and optimizing drilling parameters had become an urgent research hotspot in the field of drilling engineering. Xu et al[1] chose 8 parameters as input variables for the mechanical drilling speed prediction model. They employed a genetic algorithm random forest model and found that it yielded higher accuracy in predicting drilling speed. HEGDE C et al[2] used a data-driven method based on the random forest algorithm to establish a drilling speed model, bit torque model, and mechanical specific energy model. The optimal drilling parameters were obtained by taking drilling pressure, flow rate, bit rotation speed, and rock strength as input parameters. Sha et al[3] introduced a microhabitat particle swarm optimization algorithm based on chaotic mutation. They combined this algorithm with a BP neural network to develop an NCPSO-BP mechanical drilling speed prediction model. Li et al[4] collected and processed drilling information and logging data from other wells in the block. They selected a BP neural network for modeling (as shown in Figure 1). The optimized operating parameters could increase drilling efficiency by 12.3%. Song et al[15] utilized real-time logging data acquired from drilling sites. They performed a comparative analysis based on root mean square error, R-squared error, maximum error, and relative error to identify the optimal intelligent prediction model for mechanical drilling speed. The results indicated that the prediction accuracy and stability of the support vector machine regression model was superior to other models.



Foreign companies like Schlumberger had developed a monitoring and optimization system for underground rock breaking conditions. This system utilized big data centers to characterize the rock breaking status of underground drill bits and optimize drilling parameters. China Petroleum Engineering Technology Research Institute Co., Ltd. had put forward a quantitative evaluation method for rock breaking energy efficiency and an optimization method for drill bit working parameters. They had also developed a drilling energy-saving and speed-up drilling navigator. In general, existing intelligent acceleration methods for drilling relied on big data-driven models. And their stability and mobility required improvement. They also did not fully consider the impact of underground conditions on drilling efficiency. To achieve widespread application, it was essential to enhance the generalization performance and reliability of intelligent acceleration methods. This could be achieved by incorporating domain knowledge while considering the constraints posed by complex underground conditions.

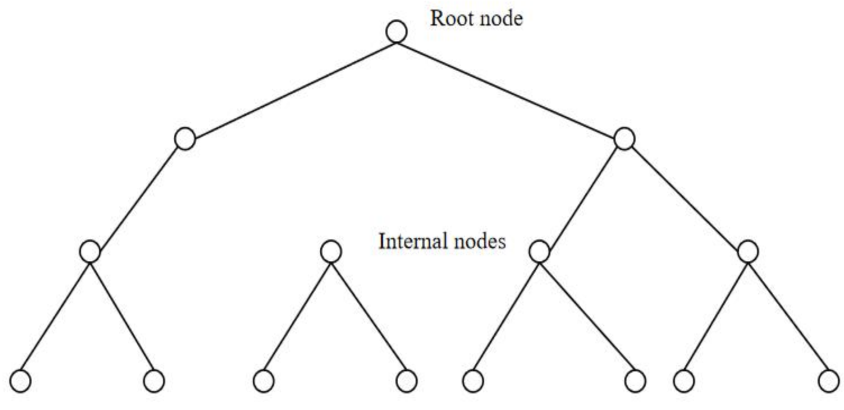
2.2 Intelligent optimization and closed-loop control of wellbore trajectory

The optimization design of wellbore trajectory was the foundation of trajectory control. Early track optimization designs were mostly focused on single objectives. Z LYU et al[6] utilized the fast marching method to optimize the wellbore trajectory of multi-branch wells in three-dimensional heterogeneous sandstone reservoirs. Their objective was to maximize the production capacity per unit length of the wellbore. Wang et al[7] used a snake shaped optimization algorithm to optimize multiple objectives such as trajectory length and resistance through geometric analysis and force balance analysis of wellbore trajectory. Atashnezhad et al[8] improved the classic optimization algorithm and applied heuristic algorithms to establish an optimal model for wellbore trajectory.

Wu et al[9] introduced a large closed-loop servo control intelligent guided drilling method. This method drew inspiration from the theoretical and technical architecture of autonomous vehicles. Yan Tie et al[10] designed a three-dimensional intelligent wellbore trajectory. In terms of trajectory control, Liu et al[11] simulated the underground environment and conducted research on real-time control of wellbore trajectory based on reinforcement learning. In 2021, Schlumberger introduced autonomous directional drilling technology. This innovative technology enabled independent decision-making and control, and allowed for autonomous guidance in any well section. Sinopec Group had developed a latitude and longitude rotation geological steering drilling system. In experimental wells, this system had achieved a drilling rate of 96% for high-quality reservoirs, representing an overall international advanced level. In summary, the multi-objective optimization design method for wellbore trajectory did not yet possess a deep integration of reservoir distribution and string status. Furthermore, its on-site application was not yet mature. Coordination and optimization of wellbore trajectory control with drilling speed were still necessary to achieve effective control at higher drilling speeds. This would offer technical support for achieving optimal and efficient drilling of long horizontal wells.

2.3 Intelligent warning and dynamic control of drilling risks

Real time diagnosis, early warning, and intelligent control of drilling risks were the foundation for safe and efficient drilling. Since 2010, scholars both domestically and internationally had established intelligent diagnostic and early warning models for drilling risks. These models used classic machine learning algorithms, which had significantly improved the accuracy of drilling risk diagnosis. Liu[12] used principal component analysis to reduce the dimensionality of input parameters, which greatly improved the computational efficiency of the model. Ge et al[13] developed an intelligent overflow warning model based on a random forest algorithm(as shown in Figure 2). The model utilized three omen parameters: annular flow rate, annular pressure, and annular temperature to classify and predict the severity of the overflow.



DUAN et al[14] developed different input parameter combinations based on the type of operating conditions. This improved the accuracy of gas invasion warning. LIANG et al[15] employed a genetic algorithm for parameter optimization instead of the traditional gradient descent algorithm. This approach enhanced the accuracy of diagnosing risks such as sticking and overflow. Since 2019, Song et al[16] had achieved accurate prediction of formation and wellbore pressure through mechanism data fusion methods. Wang et al[17] proposed an intelligent warning model for drilling tool jamming based on Support Vector Machine (SVM-IAM), which would automatically give a warning whether drilling tool jamming would occur. Domestic and foreign companies, including Schlumberger with its NDS system and Sinopec with the DrillRisk risk assessment system, had developed integrated systems. These systems incorporated expert knowledge from various fields, advanced hardware equipment, and software algorithms, which enabled real-time analysis of drilling construction conditions, efficient diagnosis and control of drilling risks. It was undeniable that the intelligent warning system for drilling risks faced the challenges of false alarms and false alarms. Therefore, improving the performance of the risk warning system could be achieved through data governance based on algorithm and scene fusion. Additionally, incorporating multi-dimensional parameter linkage mechanisms would further enhance the system's performance.

2.4 Intelligent evaluation and optimization control of cementing quality

The existing research on cementing quality mainly focused on intelligent prediction and interpretation evaluation of cementing quality. SANTOS et al[18] used Gaussian process regression algorithm to predict cementing quality, which enhanced the transferability of the model. Zheng et al[19] predicted the cementing quality of Shunbei Block based on the GA-SVR algorithm, which achieved real-time prediction of cementing quality. In terms of intelligent interpretation of cementing quality, REOLON et al[20] used the MRGC algorithm to evaluate cementing quality in real-time using acoustic and ultrasonic logging data. VIGGEN et al[21] used convolutional neural networks to identify variable density logging curves and evaluate cementing quality. Based on this, more logging data was fused and neural network algorithms were used to evaluate cementing quality. Based on the advantage of having a large amount of well history data, Zhao et al[22] utilized machine learning methods to establish a prediction model for pre-job cementing quality. This could avoid the blindness of cementing quality prediction caused by the one-sided and insufficient human experience and improve prediction accuracy. In summary, the intelligent diagnosis and evaluation methods for cementing quality were gradually maturing. But there was less research on the prediction and optimization methods for cementing quality. Among them, real-time optimization of cementing parameters and intelligent recommendation of cementing plans would become the main methods for on-site application.

2.5 Intelligent design and optimization regulation of fracturing schemes

Intelligent design of fracturing parameters, diagnosis of working conditions, and real-time optimization were hotspots in intelligent fracturing research. In terms of intelligent design of fracturing parameters, WANG et al[23] established a coal seam pressure fracturing well productivity prediction model based on a combination of recurrent neural networks and multi-layer perceptrons. And they applied physical constraints to the neural network model. Dong et al[24] established a productivity prediction model for fractured wells. The model was based on the XGBoost algorithm. By improving the loss function and introducing physical constraints, the prediction error was reduced from 11.68% to 9.68%.

In terms of fracturing condition diagnosis, currently, algorithms such as rule learning and transfer learning had been used both domestically and internationally to achieve subdivision of fracturing condition events . SHEN et al[25] established a real-time diagnosis model for fracturing conditions based on convolutional neural networks and U-Net architecture deep learning. The model was evaluated by using a confusion matrix with an accuracy of 95%. AWAD M et al[26]used the wavelet transform method to associate the energy information extracted from construction pump pressure data with the physical process of crack propagation. This provided an important means for real-time diagnosis of crack propagation information. In terms of fracturing optimization control, Zhou et al[27] analyzed the completion, fracturing and production data of a certain shale block through big data. They revealed the correlation between fracturing fluid backflow, completion properties and geological environment. FU et al[28] summarized the key parameters for optimizing fracturing flowback based on the analysis of flowback data from 7 unconventional oil and gas fracturing wells in the Anadarko Basin. Chen[29] studied the use of big data technology and various machine learning algorithms. They used intelligent optimization methods for fracturing parameters based on data models to obtain the optimal combination of fracturing construction parameters. To achieve the industrial application of intelligent fracturing technology, there were still problems such as limited data label samples and poor interpretability of models. In the future, small sample data mining and interpretable algorithms would become key research areas for intelligent fracturing design decision-making and optimization regulation technology.

2.6 Intelligent Design and Production Optimization of Well Completion Plan

Scientific management of oil and gas well could effectively extend the production life of oil wells and improve oil recovery. In recent years, domestic and foreign scholars had mainly focused on capacity prediction, production dynamic optimization, software platforms and hardware systems to carry out research. NEJAD A M et al[30] used data-driven methods to predict the production of oil and gas wells with multiple layers of co-production. Yang et al[31] improved the accuracy and stability of the model by establishing a mechanism data driven model. TARIQ Z et al[32] conducted real-time prediction of inflow profiles based on production time series data, reservoir data, ICV opening and other parameters. BELLO et al[33] optimized production plans through intelligent completion inflow control equipment. Wang Zhiming et al[34] developed a completion parameter optimization design method around a new inflow control device and intelligent completion flow mechanism. Domestic and foreign oil service companies had successfully developed various intelligent completion systems. The Baker Hughes SureCONNECT intelligent completion system combined distributed sensors and intelligent sliding sleeves to monitor and control the entire production process. The deepwater intelligent completion system independently developed by CNOOC had been applied in the South China Sea. With the gradual maturity of intelligent production capacity prediction and production dynamic optimization methods, it was urgent to accelerate the integration of intelligent methods and intelligent completion systems to further optimize the reservoir production intelligent management mode.

3. Conclusion

Currently, artificial intelligence technology was developing from perceptual intelligence to cognitive intelligence and specialized intelligence to general intelligence. The interpretability, reasoning ability and cognitive ability of artificial intelligence technology had become the focus of attention for scholars at home and abroad. The development of basic theories and key technologies for intelligent drilling would focus on the deep integration of domain knowledge and intelligent algorithms. On the basis of further improving and refining the artificial intelligence application scenario, we would promote the integration and governance of geological engineering data. Besides, we also strengthened the research and development of personalized intelligent algorithms.

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