Chapter

Application of Artificial Intelligence in Drilling and Completion

Heng Yang, Guanyi Shang, Xiaorong Li and Yongcun Feng

Abstract

In this chapter, we will delve into the applications of Artificial Intelligence (AI) in drilling and completion engineering within the oil and gas industry. The scope of this chapter will include the fundamentals of machine learning and deep learning, the essential algorithms, and the workflow of AI in drilling and completion engineering, from data collection to implementation and optimization. Furthermore, we will discuss various AI application areas, such as drilling parameter optimization, downhole environment detection, intelligent completion design, and more. Lastly, we will address the challenges and prospects of AI in drilling and completion engineering, examining issues related to data quality, model accuracy, reliability, and future development trends. This comprehensive exploration aims to provide readers with a solid understanding of the potential and limitations of AI in the drilling and completion engineering domain.

Keywords: intelligent drilling and completion, artificial intelligence, intelligent application scenarios, machine learning

1. Introduction

The application of artificial intelligence in the petroleum industry has become inevitable. In drilling and completion engineering, AI is considered a revolutionary technology that can reduce costs and significantly improve drilling efficiency (DE). In recent years, machine learning has been preliminarily applied to log processing and interpretation, such as lithology identification, log reconstruction, reservoir parameter estimation, etc., showing great potential. However, there are still many challenges to be solved in the automatic processing of multi-source and multi-scale data. Based on intelligent application scenarios, this book gives a comprehensive overview of the research status of intelligent drilling and completion, and discusses the key research areas in the future, aiming to strengthen the application of artificial intelligence technology in drilling and completion engineering.

2. Basic concepts and brief algorithm

Artificial Intelligence (AI), a specialized subset of computer science, strives to construct software capable of imitating tasks typically necessitating human

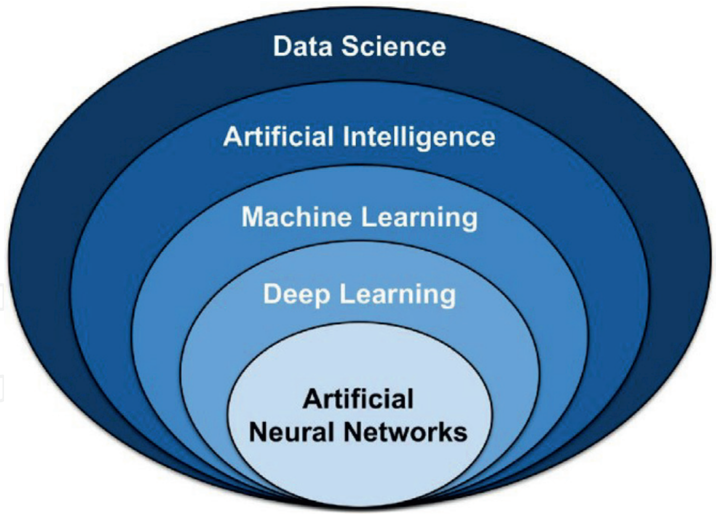


Figure 1.
The close connection and overlap between the fields of machine learning, deep learning, and artificial intelligence.

intelligence. It is part of the extensive domain of data science and integrates traditional programming with machine learning (ML), the latter featuring methodologies such as deep learning (DL) and artificial neural networks (ANN) (**Figure 1**). AI offers significant benefits, including the ability to reduce operational time based on personnel requirements and, crucially, decrease operational costs [1].

This technology has a history spanning over 16 years in the oil and gas industry, with its first application in well log interpretation dating back to 1989. In recent years, there has been a rapid increase in the number of AI tools deployed within the petroleum industry, demonstrating immense potential [2]. AI has been utilized to tackle numerous challenges within the oil and gas sector, including seismic pattern recognition, reservoir characterization, permeability and porosity prediction, PVT properties prediction, drill bit diagnosis, pipeline and well pressure drop estimation, oil well production optimization, oil well performance, portfolio management, and general decision-making operations, among others. The following will introduce the primary intelligent algorithms currently applied in drilling completion.

2.1 Machine learning

2.1.1 Classic machine learning methods

Classic machine learning methods encompass a broad range of techniques, broadly categorized into supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning. In supervised learning, algorithms learn from labeled training data, and they make predictions based on this data. Some common examples of supervised learning algorithms include Linear Regression, used for predicting a continuous output, and Support Vector Machines (SVMs) (**Figure 2**), employed for classification tasks [3]. Decision Trees and Random Forests are also frequently used, with their ability to handle both categorical and numerical data effectively. Unsupervised learning, on the other hand, operates on unlabeled data. The algorithms attempt to find inherent structures within the data without any prior knowledge. Common unsupervised learning algorithms include K-means Clustering,

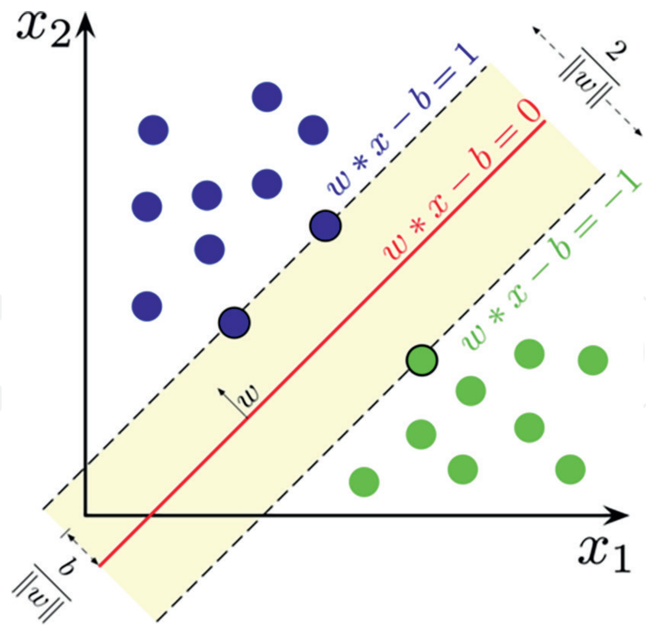


Figure 2.
SVM, maximum-margin hyperplane and margins for an SVM trained with samples from two classes.

used for grouping similar data, and Principal Component Analysis (PCA), which is often used for dimensionality reduction. Semi-supervised learning, as the name suggests, lies somewhere in between, using both labeled and unlabeled data for training—typically a small amount of labeled data with a large amount of unlabeled data [4]. Popular algorithms in this category include Label Spreading and Label Propagation. Reinforcement learning is a type of machine learning where an agent learns to behave in an environment, by performing certain actions and observing the results/feedback. Q-Learning and Deep Q Network (DQN) are two popular methods in reinforcement learning.

2.2 Neural networks and deep learning

Neural Networks form the basis for deep learning—a subset of machine learning that is based on artificial neural networks with representation learning. The primary components of these networks, artificial neurons or "nodes", mimic the neurons in the human brain, allowing the machine to learn from observational data. The simplest form of a neural network is the Feedforward Neural Network, where the information moves in one direction. More complex networks include Convolutional Neural Networks (CNNs), which are exceptionally effective for image classification tasks due to their ability to process pixel data, and Recurrent Neural Networks (RNNs) (**Figure 3**), which have "memory" and are used in tasks involving sequential data, like time series analysis [5]. This characteristic has found them extensive use in well drilling applications, where they are often employed to process depth sequences during the drilling process. Deep learning also includes architectures such as Autoencoders, which are used for unsupervised learning tasks like dimensionality reduction and anomaly detection, and Generative Adversarial Networks (GANs), a pair of networks that are used for generating new, synthetic instances of data that can pass for real data.

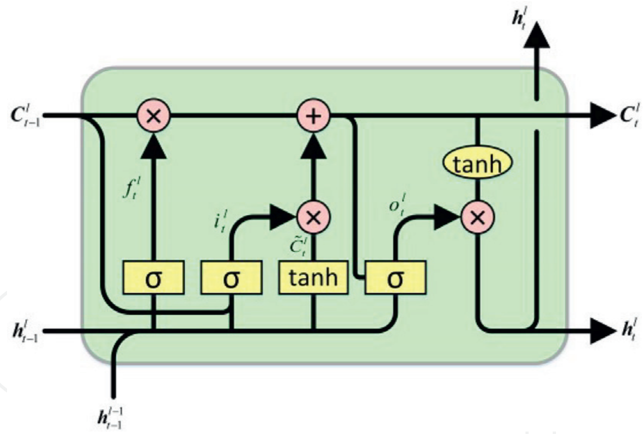


Figure 3.
LSTM unit.

3. Workflow of AI in drilling and completion engineering

In the field of Drilling and Completion Engineering, supervised learning is primarily used for predictive tasks (**Figure 4**). Its workflow can be divided into two main steps: (1) model training, and (2) inference. The training phase involves a labeled training dataset and a machine or deep learning algorithm. The learning algorithm learns how to associate the observations (also known as features) in the training dataset—for example, drilling parameters—with label information, such as formation pore pressure [6]. Specifically, the learning algorithm will use the training dataset to create or parameterize a predictive model that can then be used to make predictions on new observations.

3.1 Data collection

Well site is the main source of drilling big data, the data source of drilling big data mainly includes engineering, geological data, and main actual site video and audio data. At present, the data acquisition of drilling big data volume data source can be divided into manual input and equipment acquisition according to the acquisition

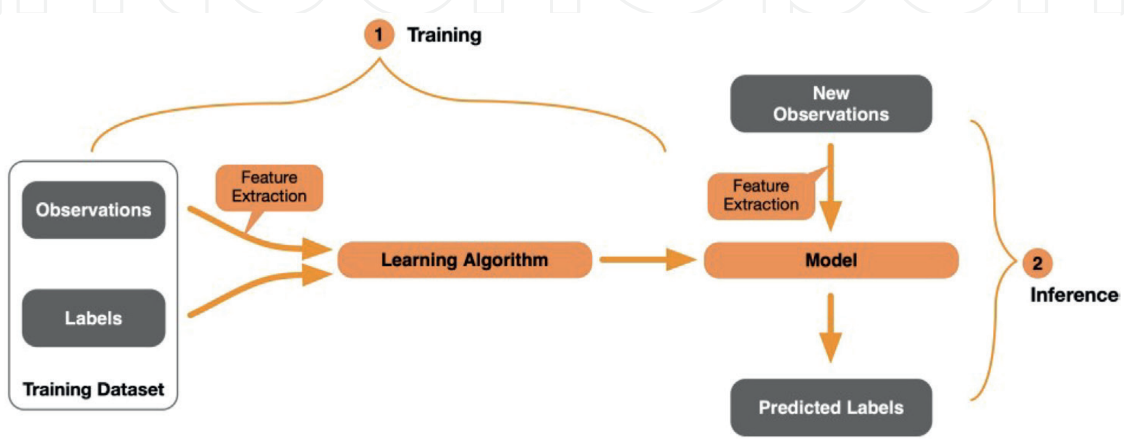


Figure 4.
Supervised learning's workflow.

methods. Manual input means that operators fill in all kinds of reports according to the rules on the customer terminal according to the requirements of the software and record the data information of the well site. Equipment acquisition refers to the way of automatically acquiring real-time data for all kinds of equipment terminal in well site by means of computer integration technology and Internet communication [7]. Drilling and completion engineering big data mainly rely on equipment acquisition, mainly including comprehensive logging instrument, drilling parameter instrument, and MWD/LWD.

3.2 Data preprocessing

The process of Data Preprocessing primarily encompasses: Data Cleansing, Data Normalization, and Correlation Analysis.

- **Data Cleansing:** The acquired data from drilling sites may contain anomalies or missing values due to environmental interference. Using this unclean data for modeling can lead to biased predictions. Therefore, it is crucial to cleanse the data before modeling, which primarily involves compensating for missing values, excluding anomalous data, and detecting redundancy.

- **Data Normalization:** In a multi-criteria evaluation system, differences can occur due to varying units of measurement or magnitude scales. Data normalization scales the data proportionally to ensure that it falls within a specific range, preserving the reliability of the experiment results.

- **Correlation Analysis:** This process investigates the relationships between different input parameters and variables. It guides the choice of modeling methods by identifying which variables are closely linked. To increase model efficiency and reduce redundancy, variables with high correlation are often excluded.

3.3 Feature extraction and selection

In the oil and gas industry, vast amounts of data are generated from various sources, including seismic surveys, well logs, production records, and reservoir simulations. Extracting meaningful insights from this data is crucial for making informed decisions and optimizing operations [8]. Feature extraction and selection techniques play a vital role in this process by reducing the dimensionality of the data and identifying the most relevant features that impact the target variable.

- **Feature extraction:** Feature extraction aims to find the best subset of features from the data. It uses methods like PCA (reducing dimension while retaining important information), ICA (separating mixed signals into independent ones), and LDA (a supervised technique for grouping and separating categories).

- **Feature selection:** Feature selection involves choosing the most relevant features for a model. It helps improve accuracy and efficiency. Techniques include the Filter method (rating features based on relevance), Wrapper method (selecting features based on a chosen algorithm's effectiveness), and Embedded method (selecting features by minimizing a loss function and adjusting feature weights).

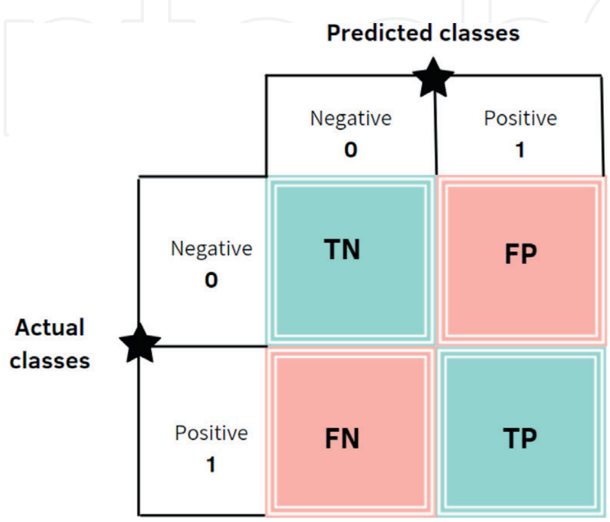
3.4 Model training and evaluation

Model evaluation and validation are crucial steps in machine learning and data science, used to ascertain and measure the performance and accuracy of a model. Throughout the model development process, it is essential to ensure that our model performs well on new data, not just on the training data.

The evaluation metrics for regression models typically include Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), R-squared (R [2]), Adjusted R-squared, Mean Absolute Percentage Error (MAPE), and Explained Variance Score. These metrics provide measures of the model's accuracy, precision, and ability to explain the variance in the dependent variable [9].

A confusion matrix is a comprehensive table that summarizes a classification model's performance by illustrating the relationship between predicted and actual classes, particularly useful for binary classification problems. The matrix consists of four key metrics: true positives (TP), false positives (FP), false negatives (FN), and true negatives (TN), which help evaluate various performance measures such as accuracy, precision, recall, and others (**Figure 5**). By analyzing the confusion matrix values, we can gain insights into the model's effectiveness in predicting positive and negative classes and identify potential errors or biases in the classification process.

The evaluation metrics for classification models, including accuracy, precision, recall, F1-score, specificity, and AUC-ROC (Area Under the Receiver Operating Characteristic Curve), provide a comprehensive understanding of the model's performance (**Figure 6**). These metrics measure the model's ability to correctly classify instances, precisely predict positive instances, sensitively identify positive instances, balance between precision and recall, accurately identify negative instances, and assess the overall classification ability of the model. Combining the confusion matrix with the insights of these evaluation indicators, the performance of classification models can be better evaluated.



$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Recall} = \frac{TP}{TP + FN}$$

$$F_1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$$

Figure 5.
Model evaluation index diagram.

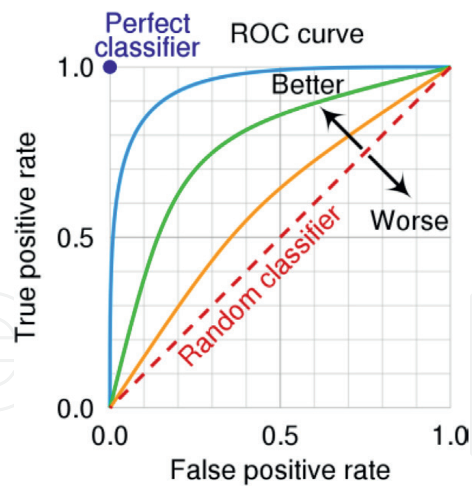


Figure 6.
ROC typical curve [10].

3.5 Result visualization and interpretation

Data visualization allows people to understand important trends and relationships in their business by transforming data into interactive visual representations. Machine learning enhances data visualization by providing more predictive and relevant data. Model interpretability refers to the ability to explain how a trained model works. It involves techniques like sensitivity analysis, local approximation, and analyzing neural network structures, and backpropagation [11]. These methods help users understand and trust machine learning models for decision-making.

4. Application areas of AI in drilling and completion engineering

Through the development of conceptualization, experience, science, and automation, drilling and completion engineering has formed a technical system guided by technical principles and methods, with equipment, tools, and materials as the means.

In drilling engineering, intelligent models have been applied for a variety of purposes, including leakage problems, intelligent prediction of ROP, optimization of well trajectory, intelligent warning of drilling risks, intelligent evaluation of cementing quality, intelligent optimization of fracturing process, intelligent completion design and overall optimization and intelligent decision-making. Among all kinds of intelligent models, artificial neural network (ANN), fuzzy logic system, genetic algorithm (GAS), support vector machine (SVM), particle swarm optimization, hybrid intelligent system, and case-based reasoning are the most widely used intelligent models in recent years. This chapter reviews the application of artificial intelligence technology in drilling engineering, considering all aspects of drilling engineering (**Figure 7**).

4.1 Intelligent prediction and improvement of penetration rate

An increasing number of wells are being drilled in deep, hard, abrasive formations, which often results in severe bit wear and lower drilling speeds. The prediction of drilling machine penetration rate plays a crucial role in optimizing drilling parameters, and

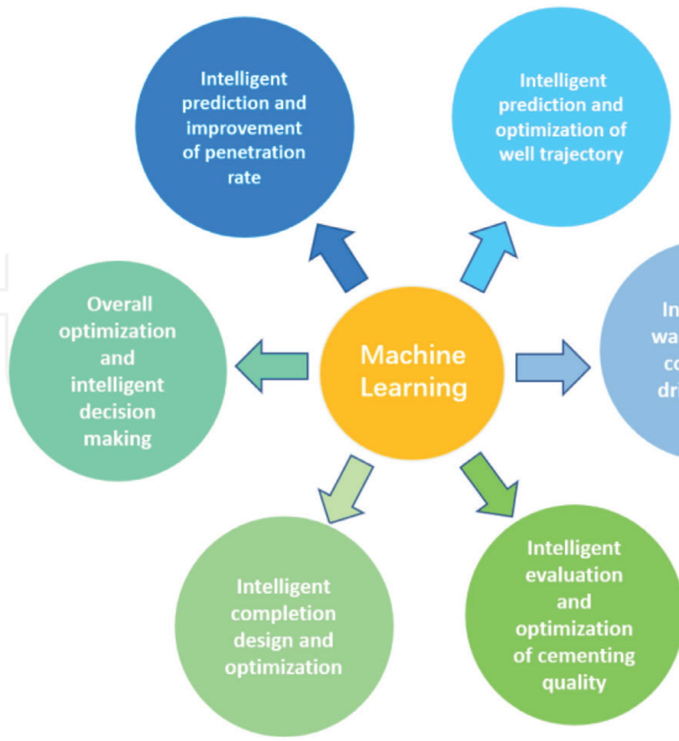


Figure 7.
Covers all aspects of drilling engineering.

can be used to check drilling data, optimize drilling rate, reduce mechanical specific energy, increase bit life, and optimize controllable parameters [12].

Mechanical penetration rate is affected and restricted by many factors, which can be divided into controllable factors and uncontrollable factors. Controllable factors refer to the factors that can be manually adjusted through certain equipment and technical means, such as ground machine pump equipment, bit size, drilling fluid properties, bit weight, and rotational speed. Uncontrollable factors refer to objectively existing factors, such as drilled formation lithology, reservoir burial depth, and formation pressure [13]. By combining the parameters of drilling fluid density, drilling parameters, bit size, drilling acceleration tools, and rock strength with various algorithms in artificial intelligence, the mechanical penetration rate of different drilling acceleration tools can be predicted, so as to evaluate the operation effect of each tool.

The accurate description of bottom hole environment based on intelligent algorithm not only provides a reference for optimizing drilling parameters and improving drilling speed, but also indicates the identification of abnormal conditions and effectively avoids the occurrence of complex accidents (**Figure 8**).

4.2 Intelligent prediction and optimization of well trajectory

Inclined, horizontal, and extended-reach wells are commonly used to efficiently develop unconventional reservoirs. Due to the highly abrasive, anisotropic, and heterogeneous nature of the formation rocks, the drilling trajectory of these wells can easily deviate from the design. Prior to drilling, the design process of the well trajectory can be optimized based on big data and artificial intelligence technology. During the drilling process, the drilling trajectory can be calculated in real time, the degree of deviation can be evaluated, and the steering controllable parameters can be optimized. Finally, the mapping relationship between the key controllable parameters

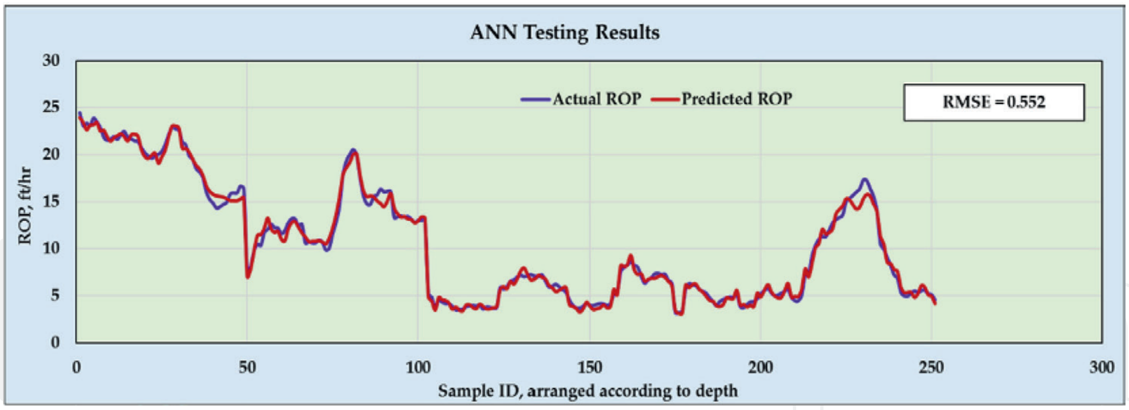


Figure 8.
Covers all aspects of drilling engineering ROP prediction using ANN technique for (A) training (750 data points) and (B) testing data (250 data points).

and the application is given to establish control instructions, forming a closed-loop control framework. Intelligent design and real-time optimization of borehole trajectory mainly include intelligent prediction of borehole trajectory, real-time evaluation and optimization of borehole trajectory, and drilling borehole trajectory control [14].

4.2.1 Intelligent prediction of well trajectory

The intelligent design of borehole trajectory is based on geological reservoir model, and intelligent technology such as computer vision algorithm can be used to optimize and automate the design process. The intelligent design process is designed to take into account parameters such as torque, resistance, and total length to maximize the contact area of the reservoir while meeting the curvature requirements. Compared with the traditional design model, the time cost is reduced. Well trajectory design is a parameter matrix optimization problem, and the optimization objectives are usually borehole length, string torque, target hit, and oil and gas production [15].

4.2.2 Real-time evaluation and optimization of wellbore trajectory

Real-time evaluation and optimization of wellbore trajectory intelligent algorithms can be used to assess the difference between the drilling trajectory and the design trajectory, and then reduce the difference by optimizing controllable parameters such as the drilling angle. The optimization of drilling trajectory is a multi-objective process in which parameters such as minimum deviation, well length, and friction are targets, while other parameters such as the deflection ability of the BHA are constraints [16]. Compared to well trajectory design, well trajectory optimization requires real-time calculation of optimization results, which requires higher computational efficiency [17]. Trajectory evaluation should not only consider the fit degree between the actual trajectory and the real trajectory, but also consider the cost, risk, and drilling stability of the wellbore.

4.2.3 Drilling well trajectory control

In the process of geosteering and rotary steering construction, experienced professionals are needed to make a lot of decisions, and manual judgment is prone to errors and errors. By using artificial intelligence technology, drilling well trajectory

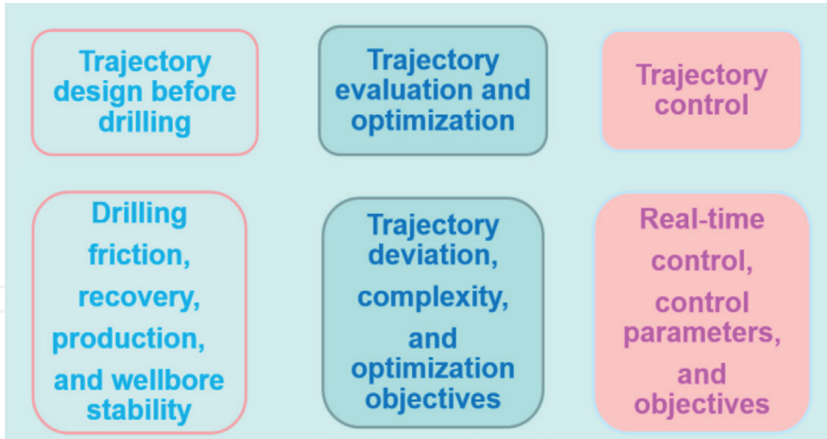


Figure 9.
Intelligent prediction and optimization of well trajectory.

guidance and control can be completely independent of human intervention, and the measurement, transmission of downhole information, and the generation and execution of control instructions can be completely automatic (**Figure 9**).

4.3 Intelligent warning and control of drilling risk

The instability of near-well formation and the imbalance of wellbore and formation interaction are the main causes of drilling accidents, such as overflow, loss, stuck drilling, and well collapse [18]. Advance prediction and real-time diagnosis are necessary conditions to avoid accidents. However, complex formation properties, such as microfractures, bottom hole high temperature and pressure, and the coexistence of kick and blowout, are the main limiting factors in accurately predicting and identifying drilling accidents [19].

At present, the intelligent risk prediction of overflow, stuck drilling, well collapse, and other problems are difficult to develop because of many factors. The well loss prediction and early warning and prevention and plugging measures based on artificial neural network, random forest, support vector machine, and case-based reasoning are widely used in the field. Lost circulation prediction problems mainly focus on loss channel, loss pressure, and loss rate, etc [7]. The research has made full use of various geological engineering parameters, accuracy, and timeliness. However, due to the serious fragmentation of loss-related data, it is difficult to collect, screen, and integrate data, and the problems of small amount of data and few types of data in the training set of the algorithm model have become increasingly prominent, resulting in the lack of on-site verification optimization. It is also necessary to further improve the accuracy and reliability of lost circulation prevention and plugging related algorithm models, accelerate the development process of expert systems, and ensure the digital and intelligent transformation and development of circulation prevention and plugging technology [20].

The artificial intelligence algorithm can comprehensively reflect the relationship between multiple factors and drilling risk and has a good prediction of logging data noise. Conversely, intelligent algorithms that are sensitive to fluctuations in data can diagnose risk more quickly. Relevant studies include pre-drilling risk prediction, risk warning and diagnosis, risk grade assessment, etc [21]. The current research is mainly focused on the early warning and diagnosis of drilling process risk, prediction and risk grade assessment (**Figures 10–12**).

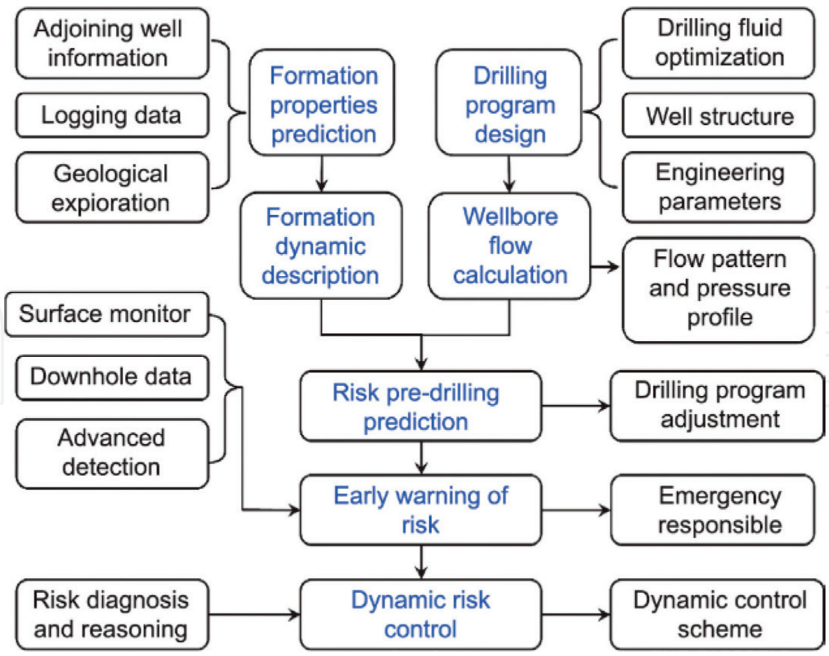


Figure 10.
Application scenarios for AI in drilling risk control.

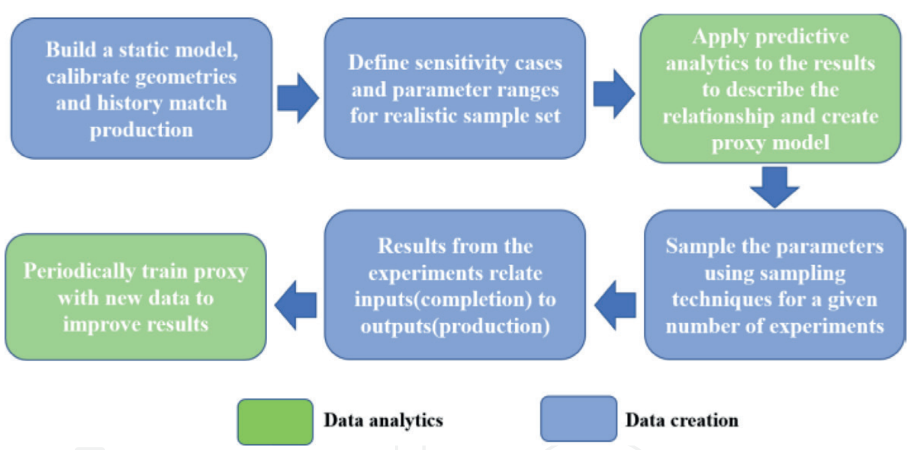


Figure 11.
Generic workflow to build a predictive proxy model for completion optimization.

4.4 Intelligent evaluation and optimization of cementing quality

The quality of cementing is directly related to the normal operation of the oil well. Therefore, the evaluation of cementing quality has become an important and indispensable link in the field of petroleum logging interpretation [23]. At the same time, the intelligent interpretation of logging data based on intelligent information processing technology can realize a higher degree of intelligence in logging interpretation and improve the accuracy and reliability of interpretation results has become a research hotspot and development direction in this field.

Among the currently used intelligent cementing quality evaluation technologies, acoustic amplitude logging technology is generally used to evaluate the cementing quality by identifying the characteristics of the first wave amplitude of the formation echo. Based on the sample advantages of a large number of well history data, a machine learning method is adopted to establish a pre-job cementing quality

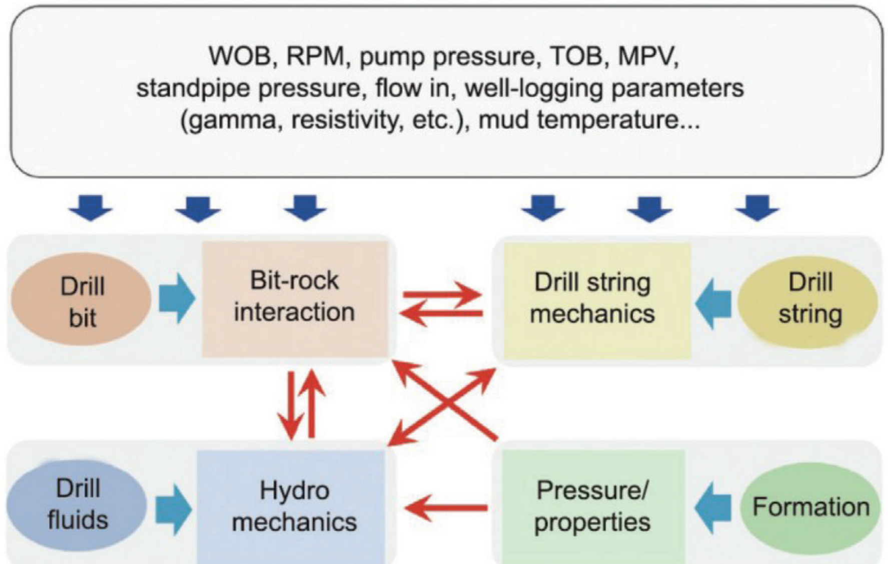


Figure 12.
Generic workflow to build a predictive proxy model for completion optimization [22].

prediction model [24]. It can avoid the blindness of cementing quality prediction caused by one-sided and insufficient human experience and improve the prediction accuracy. At the same time, the cementing design and construction scheme can be optimized before the operation to improve the effectiveness of the construction scheme and provide better guidance for the field operation and construction. Moreover, the work mode can be changed from the work mode with large research limitations, strong singleness, and heavy reliance on expert experience to the new mode of automatic data collection, data analysis, modeling, and independent prediction by machines.

4.5 Intelligent completion design and optimization

Intelligent well completion is mainly composed of downhole automation, remote sensing, and control system. Intelligent well completion is an advanced and maximized approach to production and enhanced oil recovery [25]. In intelligent well completion technology, a permanent monitoring system can be introduced into the well. On the one hand, multi-layer simultaneous mining processing can be carried out with the help of this system, and on the other hand, a certain layer can be precisely mined. The system has the functions of collecting, transmitting, and analyzing borehole production data, and can also remotely control the monitoring of reservoir performance and production performance, which is of great value in reservoir data processing. The completed data source consists of static and dynamic data. Static data includes reservoir properties and branching well structure, while dynamic data includes surface monitoring production data and downhole sensing information [26]. In the new era, the application of intelligent well completion technology is becoming more and more common, and it has been applied in horizontal wells, extended reach wells, remote wells, and so on.

In terms of intelligent algorithms, sequential regression algorithm is usually combined with numerical simulation to predict future production dynamics, and optimization algorithms and hydraulic control lines are used to optimize and control the operating state of downhole fluid control equipment such as inflow control valves [27].

These advances in smart completion-related technologies will significantly reduce costs and improve the reliability of existing technologies, effectively driving the development of smart completions.

4.6 Overall optimization and intelligent decision-making

Drilling and completion systems are complex because they consist of several closely related downhole subsystems, such as geosteering, rock breaking, hydraulics, and drillstring systems. The goal of drilling is to create holes efficiently and with high quality while maintaining low risk and cost. Therefore, drilling optimization involves multiple objectives and multiple subsystems, requiring a model that integrates coupled subsystems. The overall optimization and intelligent decision-making of the drilling process is an important scenario for the application of artificial intelligence in the field of drilling and completion [28].

This will ensure drilling safety, shorten drilling cycles, and save drilling costs.

In order to achieve this goal, it is necessary to combine physics-based and data-driven approaches, analyze the coupling mechanism of subsystems, and build mathematical models of integrated subsystems [29]. The integrated model should be dynamic and serve as the basis for drilling optimization, subject to controllable surface operating parameters and drilling risks, which means that operating parameters should not cause accidents, such as column lifting and pipe sticking. Multi-objective optimization algorithms and intelligent decision strategies must have specific objectives, including optimizing drilling rates and drilling costs. The algorithm must be fast and efficient to meet the requirements of real-time operation. Finally, a framework must be developed that integrates all models and algorithms for overall optimization and intelligent decision-making during drilling. Integrating all subsystems of the drilling process to achieve optimal performance is essential for intelligent or autonomous drilling. At present, although a lot of research has been carried out in the aspects of model construction, framework design, system development, etc [30], the research on overall optimization and intelligent decision-making of drilling process is still in its infancy.

5. Challenges and prospects of AI in drilling and completion engineering

The rapid development of artificial intelligence will inevitably cause great changes in the oil industry, but it will ultimately be the continuous evolution of the oil industry and artificial intelligence. The oil industry chain is mature, and the addition of artificial intelligence elements will significantly improve the efficiency and benefits of the industry [31]. At the same time, the future development of artificial intelligence needs to gradually transform the analysis of the “black box” into the display of the “transparent box”, that is, to deeply integrate artificial intelligence technology with the theory and technology of oil and gas engineering, and fully explain the various logical laws caused by physical, mechanical, and chemical mechanisms.

5.1 Application problems and challenges of artificial intelligence technology in drilling and completion development

Data has become a new resource, which not only promotes the development of social economy, but also promotes the continuous progress of artificial intelligence.

However, AI applications in oil exploration and development often fall into the trap of constantly upgrading equipment and software, resulting in offline machines, fragmented software, and fragmented data. To achieve industrial applications, artificial intelligence needs to have sufficient high-quality data, clear application scenarios, scientific and appropriate algorithm models, and other conditions. It is relatively easy to carry out exploratory research, but it faces many difficulties when it is applied to the industrial level [32]. Objectively, the heterogeneity of the reservoir leads to the multi-solution and uncertainty of petroleum geological problems, and it is difficult to obtain the “teaching material” (label data) for machine learning, and high-quality label data is the key to realize the industrial application of artificial intelligence technology. The acquisition cost of geological data is often high, so the data obtained are mostly “small samples”, and the amount of data cannot meet the requirements of deep learning. Due to the extremely professional and special nature of petroleum exploration and development data, general artificial intelligence algorithms cannot be directly used. When using transfer learning technology to improve the training accuracy, existing relevant pre-training models need to be referenced. Due to the particularity of petroleum exploration and development application scenarios, appropriate pre-training models and prior knowledge cannot be found in the existing resource database. All of these have hindered the progress of artificial intelligence applications to some extent.

On the subjective side, limited by the management system, the status quo of data and other aspects of the impact, artificial intelligence landing application faces many difficulties. At present, artificial intelligence research in the field of exploration and development has shown explosive growth, but the lack of systematic sorting has caused resource waste and repeated investment to a certain extent. Exploration and development data generally show the characteristics of large volume, multi-source heterogeneity, and other big data. However, “big data” is not equal to “big data”, the current oil exploration and development data standards are inconsistent, data quality is uneven, and there is no actual data sharing, which leads to the lack of data foundation for artificial intelligence applications. At the same time, the application scenario of artificial intelligence is not clear and systematic, its development goals and technical routes are not clear, and the key basic theories and technical equipment of “oil and gas + intelligence” are lacking [33]. Therefore, in the application of artificial intelligence, how to restructure the management process and realize the boosting role of artificial intelligence in improving quality, increasing efficiency, and reducing cost is a huge challenge facing the future.

5.2 The development direction of artificial intelligence application

Artificial intelligence technology will certainly provide new impetus for scientific breakthroughs in the entire oil and gas industry chain. Considering the demand of petroleum exploration and development and the research status of artificial intelligence technology, the future development of intelligent drilling and completion is to form intelligent and efficient TT&C technology and equipment with advantages of high drilling rate, high borehole trajectory control accuracy and high working reliability:

- **Smart devices.** As deep learning, natural language processing, speech recognition, reinforcement learning, and other technologies continue to successfully integrate into robots, industrial robots are gradually maturing. More and more oil companies are using robots to replace humans in dangerous operations. To date, robots have been successfully used in pipeline patrols, deepwater operations, and other high-risk operations. UAV technology has gradually been applied in exploration and development operations, especially in the field of geophysical exploration, where UAV can carry out geological exploration, data collection, video surveillance, material delivery, engineering rescue, and so on [34]. At the same time, due to the professional software embedded in the device, the device is becoming more and more intelligent. In the future, smart devices embedded with technologies such as the Internet of Things, machine vision, and deep learning will greatly reduce operating costs and improve operational efficiency.

- **Automatic data processing and interpretation.** The application of data mining and mathematical statistics technology in petroleum exploration and development is very successful and widely used in logging curve interpretation and reservoir parameter prediction. In recent years, with the continuous progress of deep learning, ensemble learning, transfer learning, and other technologies, the outstanding advantages of artificial intelligence in image processing, analysis, and prediction continue to emerge. In the future, deep learning, ensemble learning, transfer learning, strong memory learning, and other technologies are expected to be deeply applied in the automatic processing and analysis of petroleum physics, seismic images, well logging curves, digital core, production operations, and other data [35].

- **Professional software platform.** In the field of petroleum exploration and development, oil and gas professional software and information system is the carrier and core of artificial intelligence technology. Professional software is the most important research tool, the necessary achievement of expert wisdom, and the core competitiveness of oilfield service companies. With the application of AI algorithms in automatic data acquisition, intelligent processing, and analysis, some professional software packages use machine learning, machine vision, data mining, and other algorithms to further enhance the level of intelligence and are committed to realizing data sharing. Professional software packages such as Petrel, Techlog, and Eclipse continue to absorb AI technology, become more intelligent, and realize the integration of simulation and design. In the future, the research and development of AI technology will be increased for the existing well-known professional software packages in the industry to make it more intelligent.

6. Conclusion(s)

The application of artificial intelligence in the field of oil exploration and development has just started, and has not yet formed subversive results, but it has shown great potential. Drilling and completion exploration and development is faced with multiple solutions, small samples, and other problems, and the application of artificial intelligence is difficult to promote, so the application of artificial intelligence in oil exploration and development should not be fully rolled out and should be gradually promoted. The potential development direction of artificial intelligence in petroleum exploration and development is intelligent production equipment, automatic processing and interpretation, and specialized software platform. At the same time, the intelligence of the petroleum industry needs to take professional knowledge and technology as the infrastructure, and artificial intelligence is the means to achieve the optimization of industry efficiency and benefits. According to the changes of application objects, practitioners need to flexibly apply cognitive intelligence, big data, cloud computing, machine learning, deep learning, and other artificial intelligence methods to provide specific solutions for various oil and gas extraction links.

With the era of innovation and the exponential upgrading of IT technology, on the basis of the close combination of traditional oil industry knowledge and cutting-edge artificial intelligence technology, the strategic integration of creativity and creative thinking is realized, and the effective application of artificial intelligence to achieve cheap, efficient, and safe exploitation of oil and gas resources is the direction of all oil practitioners in the future.

Author details

Heng Yang, Guanyi Shang, Xiaorong Li* and Yongcun Feng
China University of Petroleum (Beijing), Beijing, China

*Address all correspondence to: xiaorongli@cup.edu.cn

References

[1] Kalogirou SA. Artificial intelligence for the modelling and control of combustion processes: A review. Progress in Energy and Combustion Science. 2003;**2003**(29):515-566

[2] Gharbi, Ridha C, Ali Mansoori G. An introduction to artificial intelligence applications in petroleum exploration and production. Journal of Petroleum Science and Engineering. 2005;**49**:93-96

[3] Radwan AE, Wood DA, Radwan AA. Machine learning and data-driven prediction of pore pressure from geophysical logs: A case study for the Mangahewa gas field, New Zealand - ScienceDirect. Journal of Rock Mechanics and Geotechnical Engineering. 2022

[4] Wei X, Zhang L, Yang H-Q, Zhang L, Yao Y-P. Machine learning for pore-water pressure time-series prediction: Application of recurrent neuralnetworks. Geoscience Frontiers. 2021;**12**(1):453-467. DOI: 10.1016/j.gsf.2020.04.011

[5] Ray SA. Quick review of machine learning algorithms. 2019 International Conference on Machine Learning, Big Data, Cloud and Parallel Computing (COMITCon). 2019. DOI: 10.1109/COMITCon.2019.8862451

[6] Dey A. Machine Learning Algorithms: A Review. International Journal of Science and Research. [Accessed: June 14, 2023]

[7] Crisci C, Ghattas B, Perera G. A review of supervised machine learning algorithms and their applications to ecological data. Ecological Modelling. 2012;**240**(none):113-122

[8] Burrell J. How the machine 'thinks': Understanding opacity in machine learning algorithms. Big Data & Society. 2016;**3**(1)

[9] Fatima M, Pasha M. Survey of machine learning algorithms for disease diagnostic. Journal of Intelligent Learning Systems and Applications. 2017;**9**(01):1

[10] Muschelli J. ROC and AUC with a binary predictor: A potentially misleading metric. Journal of Classification. 2020;**37**:696-708. DOI: 10.1007/s00357-019-09345-1

[11] Sharma D, Kumar NA. Review on machine learning algorithms, tasks and applications. International Journal of Advanced Research in Computer Engineering & Technology. 2017;**6**

[12] Banna AL, Taher A, Kaiser MS, Rahman Cho GH. Application of Artificial Intelligence in Predicting Earthquakes: State-of-the-Art and Future Challenges. 2021

[13] Hazbeh O, Aghdam SK, Ghorbani H, et al. Comparison of accuracy and computational performance between the machine learning algorithms for rate of penetration in directional drilling well. Petroleum Research. 2021;**6**(3):271-282

[14] Koryabkin V, Semenikhin A, Baybolov T, Gruzdev A, Simonov Y, Chebuniaev I, et al. Advanced data-driven model for drilling bit position and direction determination during well deepening. In: Proceedings of the SPE/IATMI Asia Pacific Oil & Gas Conference and Exhibition; 2019 Oct 29-31; Bali, Indonesia. Richardson: OnePetro; 2019

[15] Tunkiel AT, Sui D, Wiktorski T. Training-while-drilling approach to inclination prediction in directional

drilling utilizing recurrent neural networks. Journal of Petroleum Science and Engineering. 2021;**196**:108128

[16] Halafawi M, Avram L. Wellbore trajectory optimization for horizontal wells: The plan versus the reality. Journal of Oil, Gas and Petrochemical Sciences. 2019;**2**(1):49-54

[17] Li Z, Chen M, Jin Y, Lu Y, Wang H, Geng Z, et al. Study on intelligent prediction for risk level of lost circulation while drilling based on machine learning. In: Proceedings of the 52nd US Rock Mechanics/Geomechanics Symposium; Seattle, WA, USA. Richardson: OnePetro; 2018

[18] Hou X, Yang J, Yin Q, Liu H, Chen H, Zheng J, et al. Lost circulation prediction in south China sea using machine learning and big data technology. In: Proceedings of the Offshore Technology Conference; 2020 May 4-7; Houston, TX, USA. Richardson: OnePetro; 2020

[19] Alkinani HH, Al-Hameedi AT, Dunn-Norman S. Predicting the risk of lost circulation using support vector machine model. In: Proceedings of the 54th US Rock Mechanics/Geomechanics Symposium; Jun 28–Jul 1; physical event cancelled. Richardson: OnePetro; 2020

[20] Santos L, Taleghani AD. Machine Learning Framework to Generate Synthetic Cement Evaluation Logs for Wellbore Integrity Analysis. 55th US Rock Mechanics/Geomechanics Symposium; 2021

[21] Yin Q, Yang J, Liu S, et al. Intelligent method of identifying drilling risk in complex formations based on drilled Wells data. In: SPE Intelligent Oil and Gas Symposium. OnePetro; 2017

[22] Li G, Song X, Tian S, Zhu Z. Intelligent drilling and completion: A review. Engineering. 2022;**18**

[23] Tran NL, Gupta I, Devegowda D, et al. Application of interpretable machine-learning workflows to identify brittle, Fracturable, and producible rock in horizontal wells using surface drilling data. SPE Reservoir Evaluation & Engineering. 2020;**23**(4). DOI: 10.2118/202486-PA

[24] Widmer G. Using AI and Machine Learning to Study. 2004

[25] Klie H. Physics-based and data-driven surrogates for production forecasting. In: Proceedings of the SPE Reservoir Simulation Symposium; 2015 Feb 23-25; Houston, TX, USA. Richardson: OnePetro; 2015

[26] Tariq Z, Abdulraheem A, Khan MR, Sadeed A. New inflow performance relationship for a horizontal well in a naturally fractured solution gas drive reservoirs using artificial intelligence technique. In: Proceedings of the Offshore Technology Conference Asia; 2018 Mar 20-23; Kuala Lumpur, Malaysia. Richardson: OnePetro; 2018

[27] Pankaj P, Geetan S, MacDonald R, et al. Application of data science and machine learning for well completion optimization. In: Offshore Technology Conference. OnePetro; 2018. p. 18

[28] Cayeux E, Daireaux B, Ambrus A, Mihai R, Carlsen L. Autonomous decisionmaking while drilling. Energies. 2021;**14**(4):969

[29] Daireaux B, Ambrus A, Carlsen L, Mihai R, Gjerstad K, Balov MK. Development, Testing and Validation of an Adaptive Drilling Optimization System. Day 5 Fri. 12 Mar 2021;**2021**

[30] Reolon D, Maggio FD, Moriggi S, et al. Unlocking data analytics for the automatic evaluation of cement bond scenarios. In: 2020 SPWLA 61st

Annual Online Symposium. 2020. DOI: 10.30632/SPWLA-5060

[31] Mohaghegh Shahab D. Recent developments in application of artificial intelligence in petroleum engineering. Journal of Petroleum Technology. 2005;**57**(04):86-91. DOI: 10.2118/89033-JPT

[32] Goddard C, Cuadros E. Past, Present and Future Developments in CT ESP Technology in the Al Rayyan Field. International Petroleum Technology Conference. 2009. DOI: 10.2523/IPTC-13675-ABSTRACT

[33] Xiangjun Z, Xianggen Y, Zhong T. Application of artificial intelligence in transient based protection[J]. Journal-Changsha University of Electric Power Natural Science. 1999;**14**(4):340-343

[34] Qing Sun, Min Zhang, and Arun S. Mujumdar. Recent Developments of Artificial Intelligence In Drying of Fresh Food: A Review. Critical reviews in food science and nutrition. 2019;**59**(14):2258-2275. DOI: 10.1080/10408398.2018.1446900

[35] Editorial Department of Petroleum Exploration and Development. International Papers Contribution on Artificial Intelligence Promotes the Application and Development of Big Data in the Petroleum Industry[J]