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Intelligent Drilling and Completion: A Review

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ABSTRACT

The application of artificial intelligence (AI) has become inevitable in the petroleum industry. In drilling and completion engineering, AI is regarded as a transformative technology that can lower costs and significantly improve drilling efficiency (DE). In recent years, numerous studies have focused on intelligent algorithms and their application. Advanced technologies, such as digital twins and physics-guided neural networks, are expected to play roles in drilling and completion engineering. However, many challenges remain to be addressed, such as the automatic processing of multi-source and multi-scale data. Additionally, in intelligent drilling and completion, methods for the fusion of data-driven and physics-based models, few-sample learning, uncertainty modeling, and the interpretability and transferability of intelligent algorithms are research frontiers. Based on intelligent application scenarios, this study comprehensively reviews the research status of intelligent drilling and completion and discusses key research areas in the future. This study aims to enhance the berthing of AI techniques in drilling and completion engineering.

1. Introduction

In recent years, the rapid development of artificial intelligence (AI) and big data technology has attracted extensive attention from various industries [1]. Strategies for the development of AI, to seize the golden opportunity of the new technology, are being formulated by countries across the globe. In China, enhancing efforts on AI research and education has become a national strategy, and almost all industrial societies have formulated plans for intelligent transformation. As a capital- and technology-intensive industry, the oil and gas exploration and development industry has a greater demand for AI (Fig. 1), and this has attracted the attention of oil and gas companies worldwide [2]. Through cooperation with digital companies, oil companies have accelerated their transformation to an intelligent and digital age [3].

Drilling and completion engineering, a critical part of the oil and gas exploration and development process, accounts for approximately 50% of the total cost. Drilling and completion engineering will be further increased in case of complex oil and gas resources, such as offshore and ultra-deep reservoirs [4]. Drilling under these complex conditions has multiple challenges in terms of efficiency, risks, and costs, which requires technological innovation to improve efficiency and lower costs. Traditional empirical and physics-based approaches are limited and struggle to cope with increasingly complex drilling processes [5], such as the precise characterization of a complex reservoir and real-time optimization of the drilling process. AI and big data technologies have significant advantages in solving complex problems with strong nonlinear fitting and information-mining abilities. Therefore, intelligent drilling and completion technology is regarded as a transformative technology and has become a hot spot in the research and development of oil and gas industries.

Intelligent drilling and completion implies using big data, AI, information engineering, control theory, and other advanced transformative technologies in the drilling and completion process. It is expected to realize advanced detection, closed-loop control, precision steering, and intelligent decision-making through automated equipment to significantly improve drilling efficiency (DE) and reduce drilling costs. Intelligent drilling and completion technologies can be categorized into two branches: intelligent algorithms and intelligent equipment. Intelligent algorithms use AI algorithms to solve nonlinear and other complex problems and provide optimization and control schemes, providing necessary instruc-

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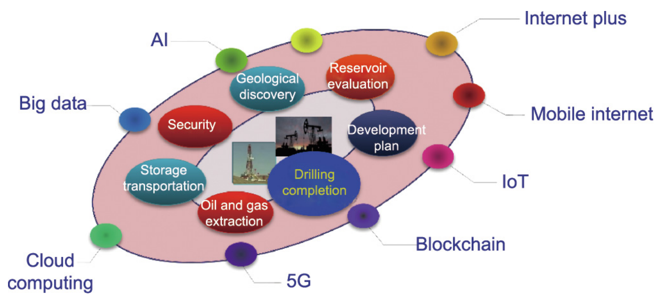

Fig. 1. Intelligent oil and gas engineering. The definitions of the abbreviations in this and subsequent figures can be found in the section "Abbreviations" at the end of the manuscript.

tions and assistance for intelligent equipment. Intelligent equipment provides data sources and hardware support to establish and verify intelligent models. In this study, a comprehensive investigation and analysis of intelligent algorithms was conducted to determine the development status of, and trends in intelligent drilling and completion.

The application scenarios for AI in the intelligent drilling and completion process are first defined, and then scenario-specific algorithms and other research content, research gaps and future works, are reviewed. This study serves as a comprehensive review for researchers in intelligent drilling and completion, clarifies AI application scenarios, and provides an important reference for the development of intelligent drilling and completion. The definition of each abbreviation used in the manuscript can be found in the "Abbreviations" section at the end of manuscript.

2. Intelligent application scenarios and research status

The application scenarios for AI in drilling and completion engineering refer to the use of AI technologies in certain engineering processes, including engineering conditions, data sources, and algorithms. This study divided intelligent drilling and completion into seven scenarios based on the engineering section and objectives, as shown in Fig. 2.

2.1. Intelligent prediction and enhancemental of drilling rate

An increasing number of wells have been drilled in deep, hard, and abrasive formations, generally resulting in severe bit wear and low drilling rates. It is also challenging to dynamically manipulate drilling parameters to ensure an ROP. The enhancement of the ROP requires intelligent algorithms to accurately characterize the drillability of the formations, select the best bit, and optimize the controllable parameters (Fig. 3).

2.1.1. Downhole environment perception

Environmental perception is the foundation of ROP enhancement. The formation lithology and bit wear can be accurately diagnosed using intelligent classification and regression algorithms. An accurate description of the bottom-hole environment, based on intelligent algorithms, is a reference for the optimization of drilling parameters and enhancement of the drilling rate. Conversely, it could also indicate identifying abnormal conditions and avoiding complex accidents. As shown in Table 1 [6–13], current studies on intelligent perception of the downhole environment mainly focus on the properties of the formation rock and bit wear.

The definitions of the abbreviations in this and subsequent tables can be found in the section "Abbreviations" at the end of the manuscript.

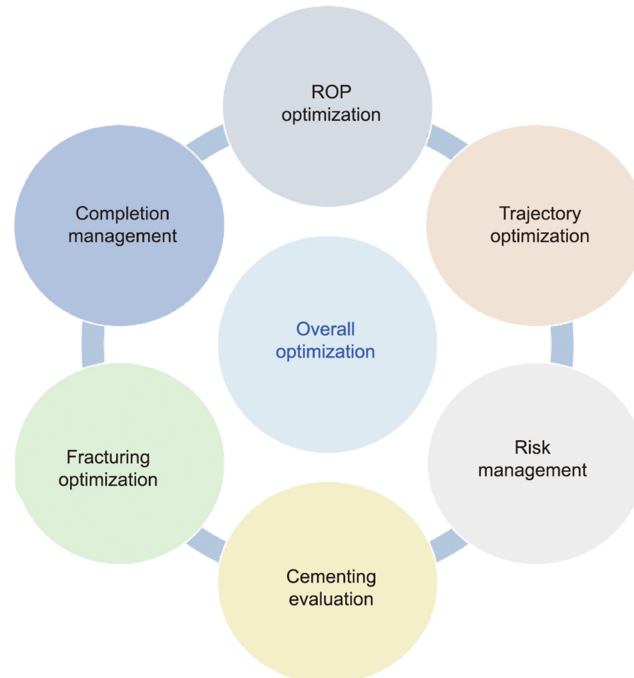

Fig. 2. Intelligent application scenarios in drilling and completion.

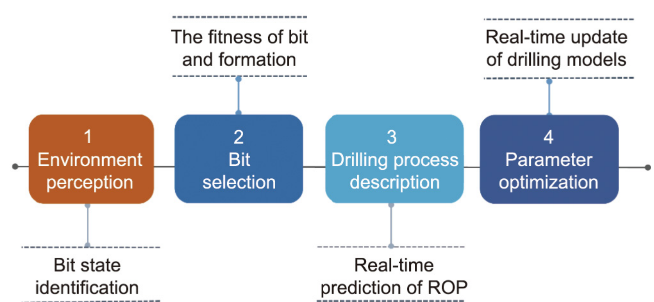

Fig. 3. Intelligent prediction and enhancement of ROP.

2.1.2. Optimization and design of drilling bit

The drill bit and bottom-hole assembly are critical to the rock-breaking process. Bit selection and optimization not only select a suitable bit based on the lithology of formation, but also reveal the rock-breaking ability of different drilling tools, which guides the design of new high-performance bits. AI technology facilitates the selection of a suitable bit structure to ensure rock-breaking efficiency and bit stability. Numerous studies have been conducted on bit selection, bit optimization, and bit wear management, as presented in Table 2 [14–20].

2.1.3. Prediction and optimization of ROP

AI technology can discover the complex mapping relation between the ROP and impacting factors such as formation properties, bit characteristics, and drilling parameters, which is superior to the capability of physics-based models. It is not subject to the limitation of expert knowledge, and it can not only accurately predict the drilling rate of various conditions, but also provide optimized drilling parameters with real-time downhole conditions to obtain the optimum ROP and avoid downhole risks. Optimization algorithms and hybrid models are the main methods of improving the accuracy of the ROP prediction (as presented in Table 3 [21–30]).

Table 1
Downhole environmental perception.

Application	Authors	Algorithms	Inputs	Contents/innovation
Prediction of drillability	Gamal et al. [6] and Asadi et al. [7]	ANN	Includes WOB, RPM, and GA	Combination of mechanism model and ANN algorithm
	Li and Cheng [8]	GA and ANN	Bit type, drilling time, rotation, WOB, etc.	IGA–ANN avoids the local convergence in classical GA
Prediction of bit wear	Asadi [9]	ANN	UCS, BTS, and rock brittleness	Combination of mechanism model and AI algorithm
	Sirdesai et al. [10]	MVRA, ANN, and ANFIS	Includes compressive and tensile strength and porosity	Comparison of various algorithms
	Kahraman et al. [11]	Regression analysis	Includes UCS and BTS	Predict the value of CAI
	Lakhanpal and Samuel [12]	Adaptive data analytics	Drilling parameters and ROP	Using EMD
Prediction of lithology	Zhekenov et al. [13]	RF	RPM, ROP, WOB, TOB, and SPP	Integrating ML with the mechanism

Table 2
Design and optimization of drilling bit.

Authors	Methods/algorithms	Inputs	Contents/innovation
Batruny et al. [14]	ANN and Monte–Carlo	WOB, RPM, hydraulic, and formation properties	ML-assisted bit selection and optimization
Abbas et al. [15]	ANN and GA	Nineteen parameters (i.e., geology, bit)	Drill bit selection and optimization
Tortrakul et al. [16]	Big data analysis	Database of neighboring wells	Bit and BHA selection
Okoro et al. [17]	ANN, PCA, and PSO	Drill bit images and drilling parameters	Drill bit selection
Rashidi et al. [18]	Clustering algorithm	Drilling parameters	Drill bit design
	Physics-based models	Real-time drilling parameters	Bit wear evaluation
Gidh et al. [19]	ANN	Drilling parameters of neighboring wells	Bit wear prediction and management
Losoya et al. [20]	KNN, RF, and ANN	Includes WOB, RPM, TOB, ECD, and MSE	Drilling condition recognition

Table 3
Intelligent prediction of ROP.

Authors	Methods/algorithms	Inputs	Contents/innovation
Liao et al. [21]	ANN	Thrust, RPM, flushing media, and compressive strength	Bee colony optimize ANN
Mehrad et al. [22]	COA, PSO, GA, SVR, MLP, and LMR	UCS, FR, WOB, depth, MD, and RPM	Use a variety of algorithm
Gan et al. [23]	Hybrid SVM and eight other methods	Depth, WOB, RPM, and FR	A hybrid model
Anemangely et al. [24]	MLP–COA and MLP–PSO	Rotary speed, WOB, and FR	MLP is combined with COA and PSO
Abbas et al. [25]	ANN	MD and other 19 parameters	Features are optimized using FSCARET
Hegde et al. [26]	Integrated RF, ANN, and linear regression.	WOB, RPM, and FR	A better integration model
Han et al. [27]	ANN and LSTM	Includes well logging and mud logging data	Timing relation of ROP
Sabah et al. [28]	DT, RF, SVM, MLP, RBF, and MLP–PSO	Includes WOB, RPM, and FR	Comparison of multiple prediction models
Soares and Gray [29]	RF, SVM, and ANN	Depth, WOB, RPM, and FR	The RF has higher accuracy
Diaz et al. [30]	MR and ANN	Includes WOB and normal compaction	Fast Fourier transform improves the model

The prediction and optimization of the ROP are inseparable because the prediction results are an important reference for optimization. ROP optimization is an extension of ROP prediction, whereby optimal drilling parameters (e.g., WOB, rotational speed, and FR) are obtained in real time using optimization algorithms (Table 4 [31–40]).

2.2. Intelligent prediction and optimization of a well trajectory

Deviated, horizontal, and extended-reach wells are commonly used for efficiently developing unconventional reservoirs. The drilling trajectories of these wells are prone to deviate from their design owing to the high abrasiveness, anisotropy, and heterogeneity of the formation rocks. Before drilling a well, the design process of the well trajectory can be optimized based on big data and AI technology. During the drilling process, the drilling trajectory can be calculated in real time, the degree of deviation evaluated, and steering controllable parameters optimized. Finally, the mapping relationship between the key controllable parameters and applied control instructions is established to form a closed-loop control framework. Intelligent design and real-time optimization of a borehole trajectory mainly includes intelligent prediction of the borehole trajectory, real-time evaluation, and optimization, and real-time control of the steering parameters (Fig. 4).

2.2.1. Intelligent design of a well trajectory

Based on the geological reservoir model, a well trajectory design process can be optimized and automated using intelligent technologies, such as computer vision algorithms. The intelligent design process aims to increase the contact area of the oil layer as much as possible while meeting the curvature requirements, considering torque and drag, total length, and other targets. This reduces the time costs compared to traditional design models. As shown in Table 5 [41–51], the borehole trajectory design is an optimization problem of the parameter matrix, including deviation depth and deviation length, and the optimization objectives are usually borehole length, drill string torque, target hitting, and oil and gas production.

Table 4
Intelligent optimization of ROP.

Authors	Methods/algorithms	Inputs	Contents/innovation
Hegde and Gray [31]	RF and PSO	Includes WOB, RPM, flow-rate, and rock strength	Coupling ROP, MSE, and TOB models
Arabjamaloei and Shadizadeh [32]	ANN and GA	Includes bit type, RPM, WOB, bit tooth wear, and ECD	GA optimized ANN to obtain the optimal parameters
Bataee and Mohseni [33]	ANN, LM, and GA	Includes bit diameter, depth, WOB, RPM, and MW	Using GA to optimize real-time drilling parameters
Gan et al. [34]	Nadaboost–ELM and RBFNN–IPSO	Includes FD, depth, SWOB, RPM, and MW	A novel two-level intelligent modeling method
Oyedere and Gray [35]	LR, LDA, QDA, SVM, and RF	Includes WOB, FR, RPM, and UCS,	The best classifier for each formation
Hegde et al. [36]	RF and gradient ascent	Includes WOB, RPM, and UCS	Consider the effect of drilling vibrations
Momeni et al. [37]	ANN and GA	Includes hole size, WOB, RPM, and MW	Using ROP model to optimize bit
Jiang and Samuel [38]	BRNN and ACO	Includes depth, WOB, RPM, mud FR, and GR	ACO and BRNN were combined to optimize ROP
Zhang et al. [39]	*K*-means	Includes depth, AC, GR, density, and UCS	Enhancing ROP with lithology
Moazzeni and Khamehchi [40]	ROA	Includes WOB and MSE	Use ROA algorithm to optimize ROP

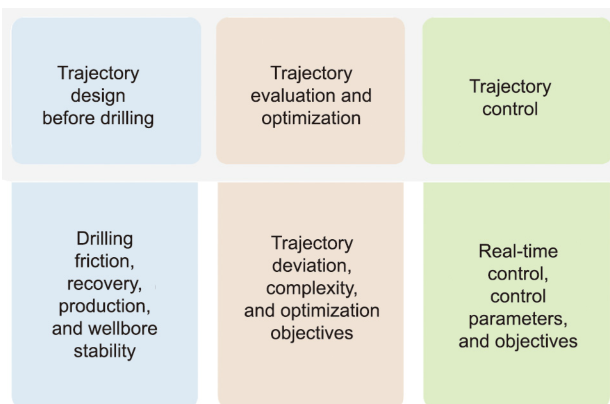

Fig. 4. Intelligent prediction and optimization of a well trajectory.

2.2.2. Real-time evaluation and optimization of a wellbore trajectory

The difference between a drilling trajectory and the designed trajectory can be evaluated using intelligent algorithms, and it can be subsequently reduced by optimizing controllable parameters such as the drilling angle. The optimization of a drilling trajectory is a multi-objective process, where parameters such as the smallest deviation, well length, and friction are objectives, and others such as the deflecting capacity of the BHA are constraints. In contrast to a well trajectory design, a wellbore trajectory optimization requires real-time calculation of the optimization results, which requires higher computational efficiency. The trajectory evaluation not only involves the fitness between the actual and real trajectories, but also considers the cost, risk, and drilling stability of the wellbore (Table 6 [52–60]).

2.2.3. Intelligent decision-making and closed-loop control of a wellbore trajectory

A control model must be established to construct an optimized well trajectory. The model discovers the mapping relationship between the key controllable parameters (i.e., the applied control instructions) and the holding, building, and dropping of the angles. Subsequently, closed-loop control can be realized using highly efficient downhole data transmission technology and intelligent tools (e.g., BHA and bit).

Trajectory control is a combination of the control strategy and tool (Table 7 [61–65]), and it requires specific control methods to be designed according to the BHA or steering tool. Furthermore, information on real-time logging and LWD is required for trajectory control.

2.3. Intelligent warning and control of drilling risks

Intelligent management of drilling risk involves achieving accurate characterization of formation properties, dynamic prediction of wellbore flow behavior, early warning, efficient control of dril-

Table 5
Intelligent design of a well trajectory.

Authors	Algorithms	Objectives	Contents
Wang et al. [41]	Computer vision	Images showing oil and gas distribution	Consider the reservoir-encountered rate as the target and the build-up rate as the constraint
Selveindran et al. [42]	LSTM	Well depth, inclination angle, and azimuth angle	RNN classifies wells with similar trajectories
Lee et al. [43]	GA	Production rate and cost	Improving both profit and cumulative production
Vlemmix et al. [44]	Gradient-based search method	Net present value	Significant improvement in NPV of the well
Zheng et al. [45]	MOC–PSO	Length, torque, and well strain energy	Constructed neighbors affected the search
Mansouri et al. [46]	MOGA	Length and torque	The adaptive function for parameter setting
Wang et al. [47]	Heuristic algorithm	Total trajectory length, well profile energy, and target hitting	Optimal clusters sidetracking horizontal
Zheng et al. [48]	ATC	Length, torque, and profile energy	Decomposition of the objective functions yields a better result
Liu and Samuel [49]	Minimum energy method	Minimum well profile energy criterion	Less electric power consumption
Li and Tang [50]	Mogi-coulomb condition with MCM	Measured depth	The stability of wellbore trajectory improved
Khosravanian et al. [51]	GA, ABC, ACO, and HS	Measured depth	ACO took less computational time than GA

Table 6
Real-time evaluation and optimization of a well trajectory.

Authors	Algorithms	Inputs/objectives	Contents
Vabø et al. [52]	Tree search algorithm	Well location and target location	Evaluating results for the optimization of drilling based on risk, value, and cost
Koryabkin et al. [53]	Lasso regression and RF	Includes block position, WOB, ROP, and SPP	The result shows MedAE of depth, inclination, and azimuth
Tunkiel et al. [54]	RNN and MLP	Logging parameters and well inclination parameters	The study can predict 23 m, while the existing methods can only predict 7 m
Noshi and Schubert [55]	ANN, AdaBoost, RF, and GBM	Includes BHA, parameters of drill bit, and logging parameters	The side forces in the form of seven dominant factors are primarily responsible
Li et al. [56]	PSO with AHP	Target hitting, lowest cost, and least drilling string friction	Numerical solutions are computed
Atashnezhad et al. [57]	PSO	True measured depth	Meta optimization helped PSO to perform better
Sha and Pan [58]	FSQGA	True measured depth	The Fibonacci series enhanced the convergence speed
Xu and Chen [59]	Bat algorithm optimizer	True measured depth	Stable wellbore trajectory designed
Halafawi and Avram [60]	MCM	Includes wellbore stability and stress determination	Optimal horizontal wellbore trajectories are designed

Table 7
Intelligent decision-making and control of wellbore trajectory.

Authors	Methods/algorithms	Inputs/objectives	Contents
Zalluhoglu et al. [61]	Physics-based and self-learning model	Real-time parameters from RSS, MWD, and LWD	Steering decisions given the BHA configuration
Sugiura et al. [62]	Physics-based models	Real-time parameters from RSS, MWD, and LWD	Saving four days compared with non-high-dogleg RSS runs
Zhang et al. [63]	Dual-loop feedback cooperative control method	Real-time parameters from RSS, MWD, and LWD	Trajectory tracking control for RSSs
Song et al. [64]	Physics-based models	Real-time parameters from RSS	Tracking-based tool faces positioning on RSS
Kullawan et al. [65]	Discretized stochastic	Real-time parameters from LWD	Decision-oriented geosteering

ling risk based on various data resources (e.g., geological detection, logging, and MWD), and AI algorithms (e.g., digital twin, computer vision, and intelligent control) (Fig. 5).

2.3.1. Intelligent characterization of formation properties

Formation properties mainly include formation pressure, stress, and permeability, which are critical to improving the ROP, avoiding risks, and stabilizing borehole walls. To improve the reliability of the formation characterization, some innovative fusion of data and neural network optimization methods have been developed (Table 8 [66–73]).

2.3.2. Intelligent description of wellbore flow behavior

Generally, a wellbore flow description involves the wellbore pressure, flow pattern, circulating pressure loss, cutting concentration, and ECD, based on real-time surface monitoring data and intelligent algorithms (Table 9 [74–85]). The wellbore structure, geothermal gradient, formation pressure, and intruding fluids complicate wellbore flow characterization. MPD or underbalanced drilling processes are the main fields for the intelligent prediction of the bottom-hole pressure and the ECD. The introduction of intelligent algorithms has significantly improved the accuracy and efficiency of downhole pressure prediction and cuttings concentration prediction, overcoming the limitations of traditional empirical models, and replacing the function of downhole sensors.

The direct combination of intelligent algorithms and wellbore flow data is a primary form of intelligent modeling. In recent years, scholars have explored new modeling approaches, such as data fusion, hybrid algorithms, and a combination of data and mechanisms, as shown in Table 9.

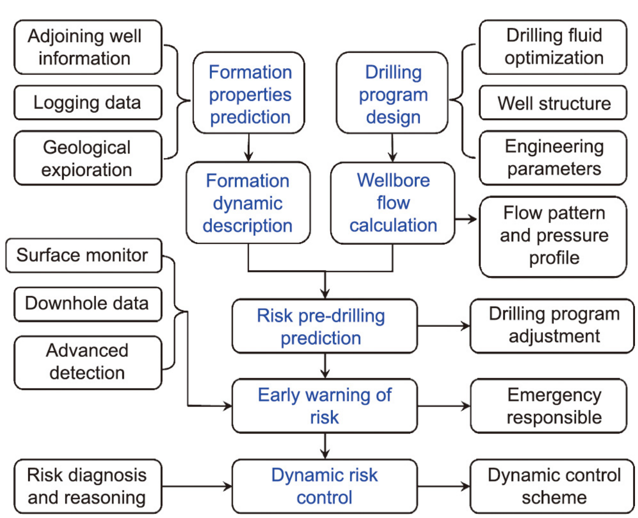

Fig. 5. Application scenarios for AI in drilling risk control.

2.3.3. Intelligent prediction and diagnosis of drilling risks

The instability of near-wellbore formation and the imbalance of interaction between the wellbore and formation are the main causes of drilling accidents, such as overflow, well loss, stuck drilling, and well collapse. Advanced prediction and real-time diagnosis are essential for avoiding the occurrence of accidents. However, complex formation properties, such as micro-fractures, high temperature and high pressure in the bottom hole, and the coexistence of kicks and blowouts, are the primary limitations of accurate prediction and identification of drilling accidents. An intelligent algorithm can reflect the comprehensive relationship between multiple factors and drilling risks while exhibiting excellent robustness to the noise of logging data. Conversely, an intelligent algorithm with sensitivity to data fluctuations can diagnose risks in faster. Related research includes pre-drilling risk prediction, risk warning and diagnosis, and risk grade assessment. To the best of the author's knowledge, existing research mainly focuses on early warning and diagnosis of risks in the drilling process, while research on prediction and risk grade assessment is still in progress (Table 10 [86–104]).

Table 8
Intelligent characterization of formation properties.

Application	Authors	Algorithms	Input parameters	Contents/innovation
Prediction of formation pressure pre-drilling	Kazei et al. [66]	CNN and LSTM	Zero-offset VSP and well-logging	Predict the rock mechanics of the lower part of the bit
Monitoring of formation pore pressure in real-time	Rashidi and Asadi [67]	ANN	MSE and DE	Using MSE and DE to predict the formation pressure
	Ahmed et al. [68]	ANN	Pump rate, SPP, RPM, ROP, torque, and WOB	Using mechanical and hydraulic parameters to monitor formation pressure
	Vefring et al. [69]	LM and Kalman filter	Pump pressure, BHP, and outlet rates	Inversion of the pore pressure based on the drilling parameters
Post-drilling assessment of formation pore pressure	Zambranoet al [70]	DT, RF, SVM, and AdaBoost	Includes gamma-ray, bulk density, and deep resistivity	Using the parameters of the normal compaction trend line as the input
	Mylnikov et al. [71]	ANN	TVD and acoustic well-logging	Using the vertical depth and sonic logging to establish a formation pressure evaluation model
	Booncharoen et al. [72]	Quantile, Ridge, and XGBoost	Includes net sand thickness, porosity, and water saturation	Considering the influence of reservoir parameters
	Naeini et al. [73]	DNN	Includes compressional velocity, gamma-ray, and density	Three neural network models are connected in series to predict geomechanical parameters

Table 9
Intelligent description of wellbore flow behavior.

Application	Authors	Algorithms	Input parameters	Main contents
BHP	Liang et al. [74]	GA–BPNN	Includes inlet and outlet flow, overflow time, and depth	Real-time prediction of BHP
	Al Shehri et al. [75]	FCNN and LSTM	Water-gas ratio, well depth, wellhead temperature, and pressure	Considering the sequence of BHP and the flow mechanism
	Fruhwirth et al. [76]	BPNN and SVM	Includes engineering parameters and combine parameters	Integration parameters enhance model generalization ability
	Zhang and Tan [77]	Naive Bayesian	Engineering parameters and combination parameters	Improved the prediction accuracy
	Li et al. [78]	Mechanism-based BPNN models	Incline angle, surface velocity, and surface tension	Broadened the model application range
	Gola et al. [79]	Grey box	Includes pump flow, throttle valve opening, back pressure, and pump FR	Combine mechanism and AI model for a stable result
	Feili et al. [80]	Neural fuzzy system	Various engineering parameters	Higher prediction accuracy
	Ashena et al. [81]	ANN	Various engineering parameters	Higher prediction accuracy
ECD	Alsaihati et al. [82] and Alkinani et al. [83]	ANN	Various engineering parameters	Various AI models were compared
	Han et al. [84]	ARIMA–BP	BHP sequence	ARIMA–BP model captures the linear and nonlinear trend
	Elzenary et al. [85]	Adaptive fuzzy neural network	ROP, inlet density, and riser pressure	FL enhances generalization

2.3.4. Intelligent management of wellbore stability

Wellbore stability is central to drilling process control. Through the control of wellbore flow to maintain the expected wellbore pressure and cuttings concentration, complex accidents can be eliminated. An intelligent control algorithm can not only regulate wellbore flow through a single parameter, such as throttle valve opening, backpressure pump FR, or mud FR, but also realize the collaborative control of multiple parameters, improve the control efficiency and accuracy, and avoid unnecessary fluctuation of wellbore pressure, which can induce secondary accidents (Table 11 [105–112]).

2.4. Intelligent evaluation and optimization of cementing quality

Cementing is an important part of well construction. Because cementing quality assessment is highly dependent on expert knowledge, intelligent cementing is proposed to achieve an accurate assessment and prediction of cementing quality, which includes cementing quality evaluation and prediction (Fig. 6). Cementing quality prediction is primarily based on logging data, and intelligent algorithms are used to correct logging information to evaluate cementing quality. The evaluation is based on a large number of acoustic amplitudes and variable density logging curves, using machine or DL algorithms to train the model to accurately evaluate the cementing quality.

2.4.1. Cementing quality prediction

Deepak Kumar Voleti of Abu Dhabi Company for Onshore Petroleum Operations Limited (trading as ADNOC Onshore) in the United States established different ML algorithms, such as RF and neural networks, based on sound amplitude, variable density logging data, and ultrasound imaging data to make predictions, and eventually adopted an integrated learning method. All the prediction models were combined to output the prediction results of cementing quality with an accuracy rate of 99.4% [113]. Santos and Dahi at the Pennsylvania State University used a Gaussian process regression algorithm for training to generate synthetic logging curves based on CBL and VDL data, which can capture the heterogeneity of cement. This research achieved good results in predicting cement bonding quality [114].

2.4.2. Cementing quality evaluation

Reolon et al. [115] used the MRGC algorithm by identifying patterns in acoustic and ultrasonic logging/graphs and then integrating MRGC into a Bayesian framework through entropy to calculate the probability of obtaining cement cementation phases, the most likely scenarios, and related uncertainties. This method can interpret and analyze cementing quality in real time. Viggen et al. [116] proposed the use of a CNN for logging data interpretation; inputted 11 types of logging data, conducted training, and

Table 10
Intelligent prediction and diagnosis of drilling risk.

Application	Authors	Algorithms	Input parameters	Main contents
Wellbore stability	Jahanbakhshi et al. [86]	PCA and ANN	Geological, engineering parameters, and mud properties	PCA implements dimension reduction of input factor
	Okpo et al. [87]	ANN	ROP, pressure, MD, and other 26 parameters	Integrated drilling, geological and reservoir information
	Lin et al. [88]	BRNN and SVM	ROP, BHA, depth, and other 20 parameters	Noise and variation in data were eliminated by EMD
	Tewari [89]	RF, ANN, and SVM	Includes FR, well angle, well depth, and ROP	Accurately predict wellbore stability in deviated wells
Drilling risk	Mohan et al. [90]	Monte Carlo	Includes well trajectories, completions, and historical events	Risk can be integrated into the system in real-time to ensure model timeliness
	Li et al. [91]	FL	Drilling monitoring parameters	Grade classification of nine risks
	Yin et al. [92]	Bayes and FL	Formation pressure, fluid density, and drilling parameters	The probability profile of risk is established by FL
Blowout and gas kick	Sule et al. [93]	Bayesian networks	Wellhead back pressure, BHP, etc.	A seven-level classification of blowout risk
	Yin et al. [94]	LSTM and RNN	Includes flow difference, pool volume, and WOB	A five-level classification of gas kick
	Yin et al. [95]	LSTM	Includes flow difference, pool volume, and WOB	Data preprocessing reduces late warning time
	Muojeke et al. [96]	ANN	Includes downhole pressure, inlet–outlet flow and density	Data from laboratory risk experiments
Lost circulation	Liang et al. [97]	ANN and PSO–SVR	Includes pore pressure, fracture pressure, and BHP	A risk level index was constructed by FL
	Pang et al. [98]	Mixture density networks	FR, density, cell volume, and hook load	Accurate warning of loss risk
	Li et al. [99]	BPNN, SVM and RF	Includes MD, filtration loss, and pump pressure	Real-time prediction of loss level
	Hou et al. [100]	ANN	Formation, fluid, and engineering parameters	Well loss probability distribution of six grades
	Alkinani et al. [101]	SVM	MW, equivalent loss density, and yield point	Classification and identification of loss degree
	Shi et al. [102]	RF and SVM	Includes flow, pressure, and temperature	Data preprocessing can reduce detection time
Stuck	Mopuri et al. [103]	CNN, SVN, and RF	Includes torque, ROP, and bit position	Reverse learning of a few sample data
	Al Dushaishi et al. [104]	DT	Includes rotation speed, BHA, and fluid parameters	Sticking prediction under different conditions

Table 11
Intelligent control of drilling process.

Application	Authors	Algorithms	Input parameters	Main contents
Wellbore pressure	Siahaan et al. [105]	Adaptive PID	Wellhead throttle valve	Based on real-time data, not limited by prior knowledge
	Zhou and Krstic [106]	Adaptive predictor control	Backpressure pump and throttle valve	Considered time delay of wellbore pressure transmission
ECD	Yin et al. [107]	Wellhead control equipment	Backpressure pump and throttle valve	Automatic management of gas kick
BHP	Pedersen and Godhavn [108]	MPC	Backpressure pump and throttle valve	Pressure control under different conditions
	Li et al. [109]	Adaptive controller	Backpressure pump and throttle valve	Robust to BHP noise
	Nandan and Imtiaz [110]	NMPC	Backpressure pump, throttle valve, and FR	Constant BHP after kick
	Nandan et al. [111]	Robust gain switching control	Backpressure pump	The robustness of the controller is enhanced
	Sule et al. [112]	NMPC	Choke manifold	Automatic management of gas kick

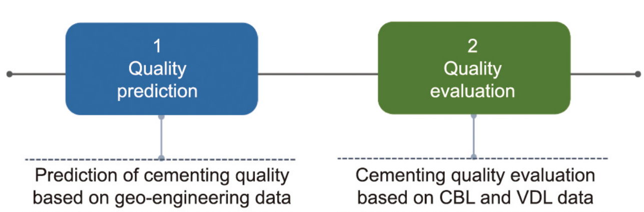

Fig. 6. Intelligent evaluation and optimization of cementing.

finally outputted six types of cementing quality with an accuracy rate of 86.7%. Viggen et al. [117] studied ML methods to automatically evaluate cementing quality and compared the self-extracting feature CNN with feature engineering to extract features artificially. The results showed that the classifier using feature engineering performed better, with accuracies of 88.9% for HI, 86.7% for CNN, and 51.6% for BQ.

2.5. Intelligent design and optimization of fracturing process

Intelligent fracturing involves the use of AI and big data technology to solve nonlinear, multiparameter, and multiobjective problems in the fracturing process. Intelligent fracturing consists of three application scenarios: intelligent design of the fracturing process, intelligent monitoring of the fracturing process, and fracturing optimization for production (Fig. 7).

2.5.1. Intelligent design of the fracturing process

The fracturing design of a horizontal well includes fracturing location and fracture parameter design. The optimization design

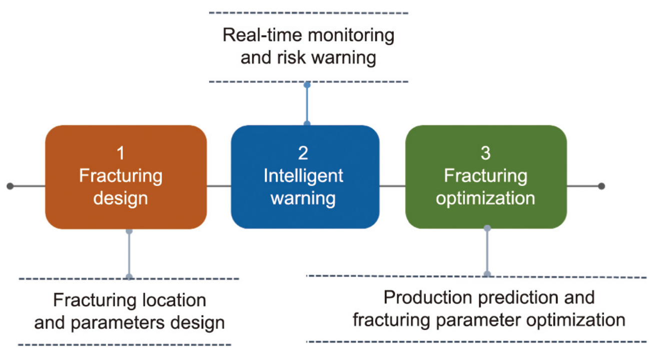

Fig. 7. Intelligent design and optimization of fracturing.

of horizontal fracturing has evolved through several methods and technologies, from simple analytical to complex numerical models from being data-driven to, now, being intelligence-driven. With big data (e.g., logging, MWD, and rock mechanics data) and intelligent algorithms (e.g., clustering, regression, and optimization algorithms), perforation fracturing optimization can be achieved (Table 12 [118–123]). Currently, the accuracy is approximately 70%–80%, which greatly improves the prediction accuracy of the productivity of fractured horizontal wells, compared with traditional methods. However, owing to the limitations of data quality and quantity, there are few examples of field applications of relevant research.

2.5.2. Intelligent monitoring of the fracturing process

Real-time monitoring is an important aspect of the fracturing process. The intelligent algorithms are gradually replacing traditional manual feature selection and anomaly monitoring, and the performance of intelligent algorithms in abnormal signal identification has greatly improved compared with traditional methods. The intelligent monitoring of the fracturing process consists of two aspects: fracturing condition identification and intelligent risk warning (Table 13 [78,124–130]).

2.5.3. Productivity prediction and fracturing optimization

Staged fracturing is necessary for efficient exploitation of unconventional oil and gas resources. The productivity prediction of fractured horizontal wells is of great significance for the evaluation of production schemes and completion optimization. With the extensive use of hydraulic fracturing technology and development of AI, the effective application of ML methods in parameter optimization design has become a trend that is expected to grow in the future. Intelligent algorithms, such as support vector machines, decision trees, neural networks, and their variants, are already being used to construct productivity prediction models (Table 14 [75,131–134]).

2.6. Intelligent design and optimization of completion

Intelligent completion is primarily composed of downhole automation, remote sensing, and control systems. The intelligent completion analyzed here is an advanced method for maximizing

Table 12
Intelligent design of hydraulic fracturing.

Authors	Algorithms	Inputs	Contents/innovation
Tran et al. [118]	KNN	Surface drilling data	Identified brittle and frackable zones
Palmer [119]	Fuzzy *C*-means	Acoustic logging and natural fracture logging	Classified similar shale formations
Xu et al. [120]	GA and adaptive evolution	Reservoir structure grid and hydraulic parameters	The azimuth and perforation clusters were optimized
Dalamarinis et al. [121]	RR and RF	Fracturing process parameters	Reduce inter-well interference and improve fracture complexity
Rahmanifard and Plaksina [122]	Genetic, differential evolution, and PSO	Includes well spacing, porosity, and permeability	PSO has the highest NPV
Gong et al. [123]	Clustering algorithm and ANN	Rock structure and geomechanical characteristics	ANN is used to identify brittle clusters

Table 13
Intelligent warning and identification of fracturing event.

Application	Authors	Algorithms	Inputs	Contents/innovation
Event recognition	Ramirez and Iriarte [124]	SVM and logistic regression	Includes pump pressure, injection rate, and proppant concentration	Automatically mark the beginning and end of hydraulic fracturing
		Decision tree		The pressure changes are analyzed and abnormal conditions are identified
	Shen et al. [125]	CNN and U-net		Mark fracturing start and end points
Pump pressure prediction	Ben et al. [126]	MLP, CNN, and RNN		Real-time prediction of wellhead pressure
Casing failure recognition	Li et al. [78]	RF		Casing failures are identified
Screen-out prediction	Maučec et al. [127]	CART		The prediction of screen-out, and identifying the affecting factors
	Sun et al. [128]	CNN–LSTM	Includes pump pressure and injection rate	Combination of physics-based inverse slope method and newly-developed ML techniques.
	Yu et al. [129]	GHMMs	Includes pump pressure, injection rate, and proppant concentration	Successful warning about 8.5 min before screen-out
	Hu et al. [130]	ARMA		The early warning rules were designed based on the prediction of pump pressure

Table 14
Productivity prediction and fracturing parameter optimization.

Application	Authors	Algorithms	Inputs	Contents/innovation
Productivity prediction	Pankaj et al. [131]	GradBoost	Includes fluid type; proppant quantity; and pumping rate and BHP	Provide the best directional response in real-time
	Bhattacharya et al. [132]	RF	Includes fracturing length, casing pressure, and tubing pressure	Optical fiber parameters are introduced to improve the accuracy of the model
	Al Shehri et al. [75]	Boost	Includes the number of stages, propping dose, and injected fluid volume	Model integration and uncertainty quantification
	Liu et al. [133]	ANN	Includes length of fracturing, fracturing clusters, and formation thickness	The underlying algorithm of time series analysis
Fracturing parameter optimization	Duplyakov et al. [134]	CatBoost	Injected fluid volume, TVD, perforation angle, and perforation spacing	The recommendation system for optimizing fracturing parameters
	Duplyakov et al. [134]	CatBoost	Includes formation thickness, angle, and formation pressure	Euclidean distance was used to find similar wells

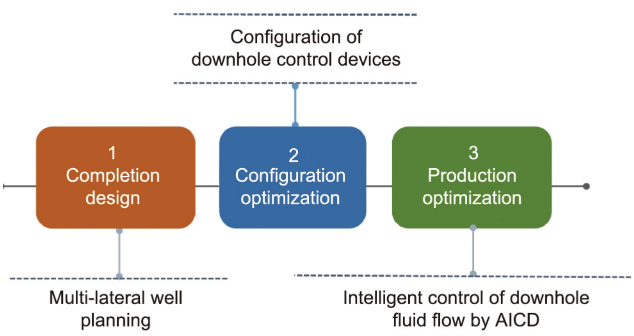

Fig. 8. Intelligent design and optimization of completion.

production and recovery using the methods shown in Fig. 8. The data sources for completion are composed of static and dynamic data. Static data include the reservoir properties and multilateral well structure, while dynamic data include surface monitoring production data and downhole sensing information. Regarding intelligent algorithms, sequential regression algorithms are usually combined with numerical simulations 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 (Table 15 [135–144]).

2.7. Overall optimization and intelligent decision-making of the drilling process

A drilling system is extremely complicated because it is composed of several tightly related downhole subsystems, such as geo-steering, rock-breaking, hydraulic, and drill-string systems, the majority of measurements are only available at the ground, and very sparse data from downholes are accessible (Fig. 9). The

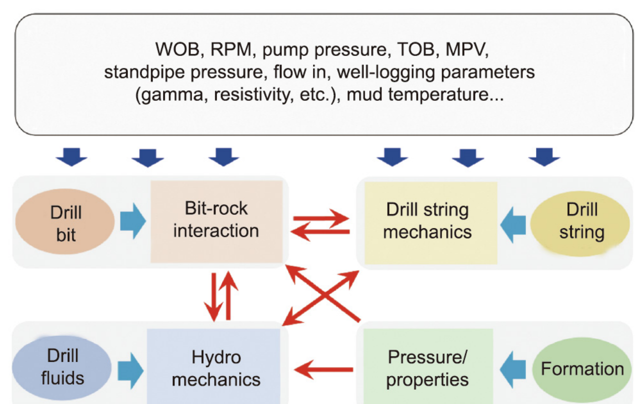

Fig. 9. Overall optimization of the drilling process.

Table 15
Intelligent completion design and optimization.

Application	Authors	Algorithms	Input parameters	Main contents
Completion design optimization	Ma et al. [135]	Augmented AI	Engineering and geological properties	Model sensitivity analysis
Production prediction	Klie [136]	RBF	Production data and time	The fusion of physics-based models and data-driven models
Inflow performance in wellbore	Tariq et al. [137]	SVM–PSO	Production data and time	The data source is a numerical simulation
Dynamic production optimization	Prosvirnov et al. [138]	–	Wellbore inflow and pressure distribution	Based on an intelligent completion system
Wellbore production profile	Chaplygin et al. [139]	RF	The number of tracers	Determine the inflow distribution based on the number of tracers
Multilateral inflow prediction	Khamehchi et al. [140]	ANN	ICV and production parameters	Prediction of downhole flow conditions
Multilateral inflow optimization	Aljubran and Horne [141]	ANN	ICV and production parameters	Optimization of downhole flow
Well and reservoir management	Bello et al. [142]	Data-driven	Downhole monitoring data	Real-time reservoir management
Completion design	Solovyev and Mikhaylov [143]	Data-driven	Production log data	Layout of the AICD
ICD and packer optimization	Goh et al. [144]	Data-driven	ICD and packer layout	Dynamic optimization of a single well

goal of drilling is to form a hole with high efficiency and quality while maintaining low risks and costs. Therefore, drilling optimization involves multiple objectives and subsystems, for which a model integrating the coupled subsystems is needed. The overall optimization and intelligent decision-making of the drilling process is an important scenario in which AI is applied in the realm of drilling and completion. It is expected to ensure drilling safety, shorten drilling periods, and save drilling costs.

To achieve this goal, a mathematical model integrating the subsystems by combining physics-based and data-driven methods and analyzing the coupling mechanism of the subsystems is required. The integrated model should be dynamic and serve as the foundation for drilling optimization. The model should be constrained by the controllable operational parameters on the ground as well as drilling risks. The latter implies that the operational parameters must not cause accidents, such as kick-off and stuck pipes. The multi-objective optimization algorithms and intelligent decision-making strategies must be implemented with specific goals, including optimizing the drilling rate, MSE, and drilling costs. The algorithms must be fast and efficient to meet the demands of real-time operation. Finally, a framework integrating all the models and algorithms must be developed to perform the overall optimization and intelligent decision making while drilling.

Integrating all the subsystems of the drilling process to perform optimally is crucial for intelligent or autonomous drilling. Although many studies have been conducted on model construction, framework design, and system development, as shown in Table 16 [145–160], research on overall optimization and intelligent decision-making during drilling is still in the early stages.

2.8. Overview of the research status

Intelligent drilling and completion are now developing rapidly, and the integration of AI with drilling and completion engineering is deepening. Many studies have ranked particular models as best by comparing the performance of ML, DL, and optimization methods in specific scenarios, and have even established hybrid models to meet the needs of precision, efficiency, and systematic reasoning. The fusion of physics-based and data-driven models has become a popular approach, which overcomes the limitations of the mechanism model, improves the stability of the data model, and reduce the interference of data noise. Common methods include reconstructing the neural network topology with mechanism knowledge, constructing loss functions under mechanism constraints, and sharing and complementation of input data. In the complex drilling process with multisystem coupling, the single-objective optimization method has obvious limitations and cannot achieve global optimization. According to the scenarios of drilling and completion, the coupling of multiple process models is realized with an optimization algorithm to realize multi-objective optimization of the drilling process and global optimization.

3. Prospects and challenges of intelligent drilling and completion

Despite the rapid development of intelligent drilling and completion, challenges remain to be addressed. Future work on intelligent drilling and completion should focus on data processing, intelligent methods, modeling methods, and application requirements (Fig. 10).

3.1. Standards and methods for data processing

Drilling and completion data are multisource and multiscale, and include micrometer-level formation pore structures and kilometer-level geologic mechanisms, as well as dynamic data from real-time monitoring and static data of formations and reservoirs. The data types are varied, and include numerical values, text, and pictures. The dynamic integration of this information is a necessary for the development of intelligent drilling and completion. Monitoring information in complex environments, such as downholes and formations, has considerable noise, anomalies, and vacancy values. Automated data governance methods and processes are critical for data-driven modeling and optimization, and data processing standards drive the application of data processing methods.

3.2. Intelligent algorithms and techniques

While computer vision can be used to process image information, it is also an important technology for digital twin visualization. Digital twin visualization, with its hypothetical capabilities, will effectively improve risk warnings and intelligent decision-making. The knowledge graph also connects different business scenarios, enhancing overall control over drilling and completion business networks. The edge-cloud integrated computing method will further release the potential of computing power for

Table 16
Overall optimization and intelligent decision-making of drilling process.

Authors/institute	Scope	Involved systems	Contents/innovation
Shishavan et al. [145]	MPD	Rock-breaking and hydraulic system	Combining ROP and BHP into a comprehensive controller for MPD
Ambrus et al. [146]	Model building	Rock-breaking and drill-string system	Modeling bit-rock interaction and drill-string dynamics
Zhou et al. [147]	Drilling optimization	Rock-breaking and hydraulic system	Multi-objective optimization and decision-making combing ROP and MPV
NORCE [148–150]	Autonomous drilling	Includes rock-breaking, drill-string, and hydraulic system	Autonomous decision-making system while drilling
Texas A&M University [151,152]	Drilling simulator	Includes rock-breaking, drill-string, and hydraulic system	Drilling simulator development
University of Stavanger [153–155]	Autonomous drilling rig	—	Designing a small-scale autonomous drilling rig and control system
Mayani et al. [156] Mayani et al. [157] Wanasinghe et al. [158]	Digital twin	—	Architectures of drilling optimization, decision-making, and control based on digital twin
eDrilling [159]	Business software	Includes rock-breaking, drill-string, and hydraulic system	Real-time modeling, monitoring, optimization, and visualization of the drilling process
DrillOps [160]	Business software	—	Real-time drilling risk monitoring, optimization, and decision-making of the drilling process

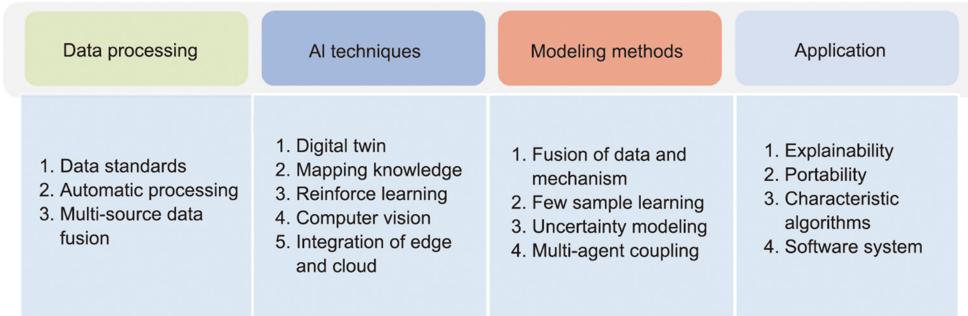

Fig. 10. Prospects of intelligent drilling and completion.

large-scale model operations and simulations, including digital twins.

3.3. Intelligent modeling

Appropriate modeling methods can improve data utilization and enhance model performance. Intelligent models incorporating prior knowledge (e.g., physical laws and expert knowledge) can guarantee accuracy and efficiency, and simultaneously improve stability and portability. Modeling methods based on the fusion of prior knowledge and big data are regarded as an important driving force in promoting the application of AI. Despite the volume of drilling and completion data, there are many few-sample scenarios, such as complex downhole conditions, that are difficult to monitor and have few reliable data about drilling accidents. Few-sample modeling can provide excellent model performance with limited data. Uncertainty analysis of the few-sample problems is helpful in understanding the nature of the problem. The coupling of agents representing physical processes to achieve accurate characterization and global optimization of drilling and completion processes will become an essential requirement for intelligent drilling and completion.

3.4. Intelligent application requirements

Interpretability and transferability of intelligent algorithms are two critical problems in the application of AI. In combination with real drilling and completion scenarios, interpretable and transferable methods for intelligent models should be explored to form unique models suitable for specific drilling and completion scenarios. Furthermore, the development of reliable intelligent models in business software can accelerate the development of intelligent models.

4. Conclusions

Intelligent drilling and completion is regarded as a transformative technology and has become a hot spot or hub for development in the oil and gas industry, significantly improving DE and reducing drilling costs. In this review, seven intelligent scenarios or application areas of AI techniques in drilling and completion engineering are proposed, and the status of research in each of the scenarios comprehensively reviewed. By combining the characteristics of drilling and completion engineering and AI, key future research areas of intelligent drilling and completion are proposed.

In the future, efforts should be focused on promoting the development of intelligent drilling and completion in the following areas: ① exploring automated data management methods and standards; ② strengthening the research in intelligent methods, such as digital twins, computer vision, knowledge graphs, and reinforcement learning; ③ developing new modeling methods, such as the combination of data and mechanisms, few-sample learning, uncertainty modeling, and multi-agent coupling; and ④ building intelligent models that are interpretable and transferable. This study has provided a systemic review of intelligent drilling and completion, and is expected to spark research and establishment of intelligent algorithms.

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Compliance with ethics guidelines

Gensheng Li, Xianzhi Song, Shouceng Tian, and Zhaopeng Zhu declare that they have no conflict of interest or financial conflicts to disclose.

Nomenclature

Abbreviations

5G	The fifth generation mobile communication technology
AdaBoost	Adaptive boosting
ABC	Artificial bee colony
AC	Acoustic time difference
ACO	Ant colony optimization
ADNOC	Abu Dhabi National Oil Company
AHP	Analytic hierarchy process
AI	Artificial intelligence
AICD	Autonomous inflow control device
ANFIS	Adaptive neuro-fuzzy inference system
ANN	Artificial neural network
ARIMA	Auto regressive integrated moving average
ARMA	Auto-regressive and moving average model
ATC	Analytical target cascading
BHA	Bottom hole assembly
BHP	Bottom hole pressure
BPNN	Back propagation neural network
BQ	Bond quality
BRNN	Bayesian regularization neural network
BTS	Brazilian tensile strength
CAI	Cerchar abrasivity index
CART	Classification and regression tree
CBL	Cement bond logging
CNN	Convolutional neural networks
COA	Cuckoo optimization algorithm

DE	Drilling efficiency
DL	Deep learning
DNN	Deep neural networks
DS	Differential search
DT	Decision tree
ECD	Equivalent circulating density
ELM	Extreme learning machine
EMD	Empirical mode decomposition
FCNN	Fully convolutional neural network
FD	Formation drillability
FL	Fuzzy logic
FNN	Functional neural network
FR	Flow rate
FSCARET	Automated feature selection from "caret"
FSQGA	Fibonacci sequence based quantum genetic algorithm
GA	Genetic algorithm
GBM	Gradient boosting machine
GHMMs	Gaussian hidden markov models
GR	Gamma ray
GradBoost	Gradient boosting
HI	Hydraulic isolation
HS	Harmony search
ICD	Inflow control device
ICV	Interval control valve
IGA	Improved genetic algorithm
IoT	Internet of Things
IPSO	Improved particle swarm optimization
KNN	K-nearest neighbor
LDA	Linear discriminant analysis
LM	Levenberg–Marquardt
LMR	Linear multivariate regression
LR	Logistic regression
LSTM	Long short-term memory neural network
LWD	Logging while drilling
MCM	Minimum curvature method
MD	Mud density
MedAE	Median absolute error
ML	Machine learning
MLP	Multi-layer perceptron
MOC	Multi-objective cellular
MOGA	Multi-objective genetic algorithm
MPC	Model predictive control
MPD	Managed pressure drilling
MPV	Mud pit volume
MRGC	Multi-resolution graph-based clustering
MSE	Mechanical specific energy
MW	Mud weight
MWD	Measurement while drilling
MVRA	Multivariate regression analysis
NPV	Net present value
PCA	Principal component analysis
PID	Proportional integral differential
PSO	Particle swarm optimization
QDA	Quadratic driscriminant analysis
RBF	Radial basis function
RBFNN	Radial basis function neural network
RF	Random forest
RNN	Recurrent neural network
ROA	Rain optimization algorithm
ROP	Rate of penetration
RPM	Revolutions per minute
RR	Ridge regression
RSS	Rotary steerable system
SPP	Stand pipe pressure
SVM	Support vector machine
SVR	Support-vector regression
SWOB	Specific weight on bit
TOB	Torque on bit
TVD	True vertical depth
UCS	Unconfined compressive strength
VDL	Variable density log
VSP	Vertical seismic profile
WOB	Weight on bit
XGBoost	Extreme gradient boosting

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