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智能钻完井技术研究综述

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摘要

石油与天然气工程智能化已成为行业发展的必然趋势，其中智能钻完井技术可以大幅提高钻井效率和钻遇率，降低施工成本，被视为油气领域的一项变革性技术和前沿热点。机理-数据融合的智能建模、数字孪生等人工智能方法及其在油气钻完井工程领域的应用已取得广泛关注和关键进展，但是智能钻完井技术研究仍然处于初级阶段。在人工智能、大数据等前沿技术与油气钻完井工程深度融合的过程中，智能钻完井场景体系、多源多尺度数据治理、机理-数据混合驱动、模型可解释性、模型迁移性和不确定性建模等面临诸多挑战。为此，本文系统提出了钻完井人工智能应用场景体系，全面阐述了各场景下的智能技术及研究进展，深入探讨了智能钻完井技术未来发展的重点方向，为人工智能技术落地油气钻完井工程提供参考。

1. 引言

近年来，人工智能和大数据技术的快速发展引起了全球各行各业的广泛关注[1]。对于一项可以激发全球产业变革性发展的前沿技术，为抓住其发展的黄金机遇期，世界各国纷纷制定了人工智能技术发展的战略蓝图。在我国，加强人工智能技术攻关和教育已成为国家战略，几乎所有工业领域都制定了相应的智能化转型规划。油气勘探开发作为资本和技术密集型行业，迫切需要油气人工智能的快速发展，实现油气开发的提质降本增效[2]（图1）。当前，全球主要油气公司先后通过与数字化公司跨界合作的方式加快智能化转型[3]。

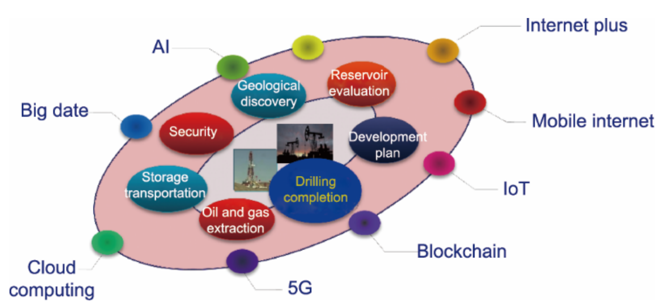

图1. 油气智能工程技术。本图及后续图中缩写的含义可以在文后Abbreviations部分找到。

钻井和完井工程是油气勘探开发的关键环节，其成本可占总成本的50%以上。对于海上、超深层等复杂油气资源，钻完井工程在效率、风险和成本等方面面临前所未有的挑战，安全高效开发的难度急剧增加[4]，亟需引进

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变革性技术实现复杂油气安全高效开发。在复杂油气的钻完井过程中，基于专家经验和机理知识的传统方法难以应对日益严峻的挑战[5]，如涉及井下环境动态变化的储层精细描述、钻井实时优化等。相比之下，人工智能和大数据技术具有较强的非线性拟合能力和信息挖掘能力，在解决复杂、非线性问题方面具有显著优势。因此钻完井人工智能技术被视为油气行业的变革性技术，已成为该领域的研究热点和前沿技术。

智能钻完井技术是基于大数据、人工智能、信息工程和控制理论等先进技术，通过地质-工程大数据、智能装备和智能算法等与钻完井场景的深度融合，实现钻完井过程的精细表征、超前预测、闭环控制、精准导向和智能决策等，从而大幅提高钻井效率、降低钻井成本。智能钻完井技术研究可分为智能化理论方法和智能化工具装备两部分。智能化理论方法利用机器学习、深度学习等人工智能算法和钻完井相关的钻-测-录多源数据，解决钻完井场景中的复杂非线性问题，如地质属性精细刻画、机械钻速高效预测等，其结果可作为科学依据辅助智能决策；智能化工具装备基于智能模型提供的钻完井方案，通过通信控制系统自动执行相关指令。智能化理论方法为智能化装备提供决策指令，智能化装备可为智能模型提供数据和硬件支撑。

本文全面综述了智能钻完井方法与技术的研究进展，回顾了智能钻完井的发展现状，提出了人工智能在钻完井工程中的七大应用场景，总结了每个场景下的智能化技术进展，梳理了智能钻完井技术研究的重点发展方向，可为智能钻完井技术发展提供参考和指导。

2. 钻完井人工智能应用场景与研究现状

钻完井人工智能应用场景是人工智能和大数据技术与钻完井工程环节深度融合的工艺过程。根据钻完井不同工程环节的施工过程和目标，本文提供了7个钻完井的人工智能应用场景（图2），并概述了不同场景下的数据情况、工程实践和智能化算法模型等内容。

2.1. 机械钻速智能预测与优化

深部地层岩石硬度大、研磨性强，岩石属性交变，容易导致严重的钻头磨损，钻井效率低、周期长，对钻井提速和钻井参数优化提出了更高要求。油气钻井智能提速的基础和关键是地层属性精准表征、井下钻具合理优化及钻井参数智能优化（图3）。

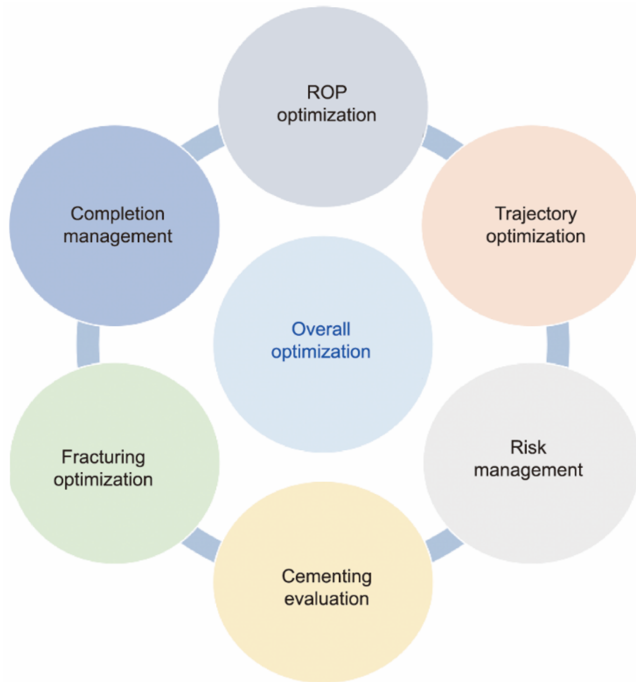

图2. 智能钻完井应用场景。

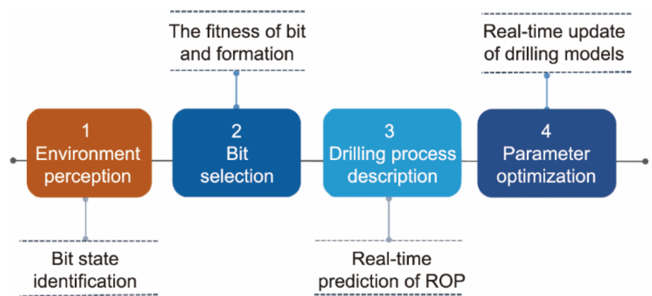

图3. 钻速智能预测与优化细分场景。

2.1.1. 井下环境感知

井下环境感知是钻井提速的基础。利用智能分类和回归算法能够准确地诊断地层岩性和钻头磨损。基于对井下环境的准确描述，一方面可采用智能算法实现钻井参数动态优化和钻井提速，另一方面也能实现钻井异常工况识别和风险管控。目前对井下环境智能感知的研究主要集中在地层岩石性质和钻头磨损特征等方面，如表1所示。

表1及后续表格中缩写的含义可以在文后的Abbreviations部分找到。

2.1.2. 钻头设计与优选

钻头和底部钻具组合的优选和优化配置是钻井高效破岩的关键。人工智能技术有助于设计合适的钻头结构、优选钻头类型，保证岩石破碎效率和钻头性能。现有研究在钻头设计优化、钻头选择和钻头磨损管理等方面进展突出，见表2。

表1 井下环境感知研究现状

Application	Author	Algorithm	Inputs	Content and 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

表2 钻头设计与优选研究现状

Authors	Methods/algorithms	Inputs	Content/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

2.1.3. 钻速预测与优化

相比于机理模型，人工智能技术在挖掘钻速与地层性质、钻头特征、工程参数等因素之间的复杂映射关系方面具备更加明显的优势。数据驱动的智能模型不仅能准确预测各种条件下的钻井速率，还能提供实时优化的工程参数，在钻进过程中获得最佳钻速。钻速模型和优化算法是提高钻速预测精度的主要手段[21–30]，见表3。

钻速优化是钻速智能预测的深化和延伸，即通过智能优化算法实时获得最优钻井参数组合（如钻压、转速和排量）[31–40]，钻井参数智能优化方面的进展主要集中在算法应用上，如表4所示。

2.2. 井眼轨迹智能预测与优化

水平井和大位移井是实现非常规油气高效开发的常用井型，然而由于地层岩石的研磨性、各向异性和非均质性，其井眼轨迹容易偏离设计轨道，复杂井眼轨迹的优化

表3 钻速预测研究现状

Authors	Methods/algorithms	Inputs	Content/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 flow rate	A hybrid model
Anemangely et al. [24]	MLP-COA and MLP-PSO	Rotary speed, WOB, and flow rate	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 flow rate	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]	FT, RF, SVM, MLP, BF, and MLP–PSO	Includes WOB, RPM and flow rate	Comparison of multiple prediction models
Soares et al. [29]	RF, SVM, ANN	Depth, WOB, RPM, and flow rate	The random forest has higher accuracy
Diaz et al. [30]	MR and ANN	Includes WOB and normal compaction	Fast Fourier transform improves the model

表4 钻速优化研究现状

Authors	Methods/algorithms	Inputs	Content/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, flow rate, 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

和调控成为亟待解决的难题。钻井之前，基于大数据和智能技术开展井眼轨道智能设计是实现井眼轨迹优化的基础；钻进过程中，结合井-地模型的实时重构和智能算法，可实现井眼轨迹实时预测和轨迹偏离程度的动态评估，进而实现调控参数的高效优化。更进一步，可建立关键调控参数与井下工具导向能力之间的映射关系，形成井眼轨迹闭环控制系统。井眼轨迹智能设计与实时优化包括井眼轨迹智能预测、实时评估优化和实时调控，如图4所示。

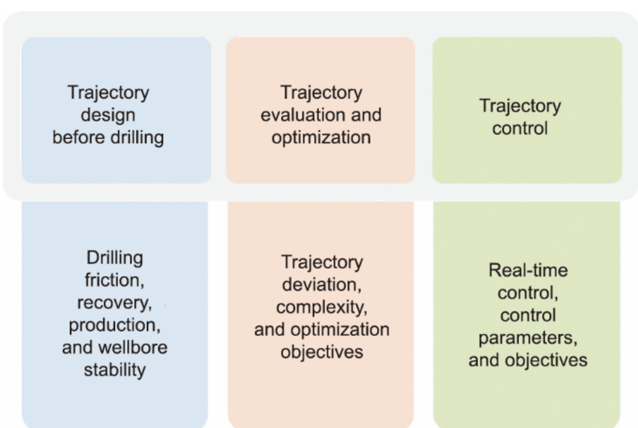

图4. 井眼轨迹智能预测与优化。

2.2.1. 井眼轨道智能设计

井眼轨道智能设计指基于地质和储层模型，结合计算机视觉、智能规划等方法实现井眼轨道的自动化设计和优化。其旨在综合考虑钻柱受力状态、延伸极限和储层钻遇率等目标，在满足井眼曲率要求的前提下尽可能增加与目的层的接触面积，相较传统轨道设计方法能够降低时间和计算成本、提高井眼轨迹的质量。井眼轨道设计实质上是一个包括井坐标、造斜点、井深和井长等参数矩阵的优化问题，其优化目标通常是钻柱延伸极限、中靶精度和采收率[41–51]（表5）。

2.2.2. 井眼轨迹实时评估与优化

井眼轨迹实时评估与优化指实时监测井眼轨迹和设计轨道的偏差，并通过智能算法进行评估和预测，结合井眼轨迹智能预测模型和优化调控算法，实现井眼轨迹的高效优化与调控，减小实际井眼与规划井眼之间的偏差。井眼轨迹优化是一个多目标优化过程，其优化目标是最小化偏差、延伸极限和钻柱受力等参数，约束条件为导向工具的造斜能力等。与井眼轨道设计相比，井眼轨迹优化需要实时计算优化结果，要求更高的计算效率，而且井眼轨迹评估也需要综合考虑钻井成本、风险和井筒稳定性[52–60]（表6）。

2.2.3. 井眼轨迹智能决策与闭环控制

井眼轨迹表征模型是实现井眼轨迹优化的基础，该模型能够挖掘关键可控参数（即导向工具控制指令）与稳斜、造斜和降斜能力之间的映射关系。而井下-地面信息的高效传输和智能导向工具等是井眼轨迹闭环控制的关键。

轨迹控制是决策下达与工具执行机构的深度组合（表7 [61–65]），需要根据BHA或导向工具能力来设计特定的控制方法，并要求实时录井数据作为支撑。

2.3. 钻井风险智能预警、诊断与调控

钻井风险智能调控指利用随钻测量和实时录井等多源数据和数字孪生、计算机视觉和智能控制等人工智能算法

表5 井眼轨道智能设计研究现状

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]	Genetic algorithm	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]	Analytical target cascading	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

表6 井眼轨迹实时评估与优化研究现状

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 and Wood [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

表7 井眼轨迹智能决策与闭环控制研究现状

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

实现地层属性的精细描述、井筒流动特性的动态预测表征、钻井风险的早期预警与高效调控，其细分场景如图5所示。

2.3.1. 地层属性智能表征

地层属性主要包括地层压力、地应力和岩石可钻性等

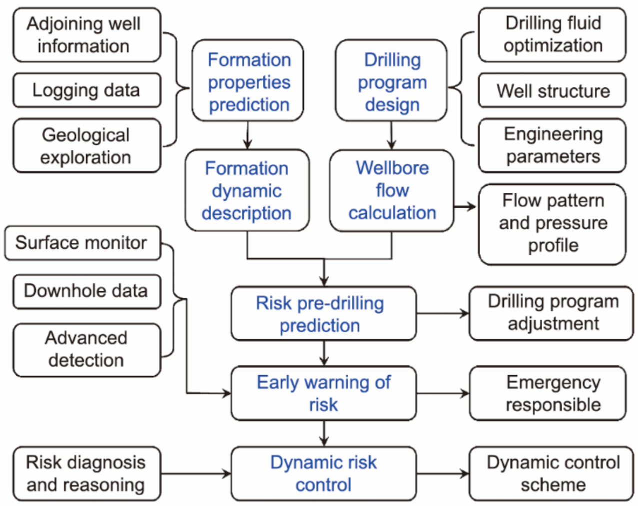

图5. 人工智能在钻井风险调控中的应用场景。

参数，对提高机械钻速、减少钻井风险、维持井壁稳定具有至关重要的作用。为提高地层表征的准确性和可靠性，国内外学者探索了不同人工智能算法和建模方式（表8 [66–73]）。

2.3.2. 井筒流动智能表征

井筒流动智能表征指基于实时地面监测数据和智能算法对井筒复杂流动特性和固相岩屑的运移规律进行动态描述[74–85]。井底压力和当量循环密度智能预测主要应用于控压钻井和欠平衡钻井，人工智能算法的引入不仅显著提高了井底压力和岩屑浓度预测的精度和效率，还克服了传统经验模型的局限性，并且有望在一定程度上取代井下传感器的功能。

目前，将井筒流动数据和智能算法结合仍是井筒流动智能建模的常见形式。近年来，学者们也探索了数据融合、算法融合和数据与机理联合驱动等一些新的建模方法，见表9。

2.3.3. 钻井风险智能预测与诊断

井壁失稳及井筒-地层压力的不平衡是造成溢流、井漏、卡钻和井塌等钻井风险的主要原因，钻井风险超前预测和实时诊断是避免钻井风险发生和恶化的关键。然而微裂缝发育、井底高温高压、井涌和井喷并存等复杂的地层和工程条件限制了钻井风险的准确预测与诊断。人工智能算法能够反映钻井风险与多种影响因素之间的综合关系，并对录井数据中的噪声具有较强的鲁棒性，可结合实时波动的数据快速诊断钻井风险。与此相关的研究包括风险钻前预测、风险预警与诊断、风险等级评估等。现有研究主要集中于钻进时风险的早期预警和诊断，而对于钻前风险预测与风险等级评估的相关研究相对较少（表10 [86–104]）。

2.3.4. 井筒稳定性智能调控

井筒稳定是井控的核心任务，钻井过程中通过控制井筒流量使井筒压力和岩屑浓度达到目标值，能够有效避免钻井复杂事故的发生。控压钻井过程中，智能控制

表8 地层属性智能表征研究现状

Application	Authors	Algorithms	Input parameters	Content/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, 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

表9 井筒流动智能表征研究现状

Application	Authors	Algorithms	Input parameters	Main content
Bottom hole pressure	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 flow rate	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	Fuzzy logic enhances generalization

算法不仅可以通过节流阀开度、回压泵或泥浆泵流量等单一参数来调节井筒流量，还可以实现多个参数的协同控制，从而提高井底压力的控制效率和精度，避免井筒压力产生不必要的波动诱发二次风险（表11 [105–112]）。

2.4. 固井质量智能评价与优化

固井是油气井建井的重要环节。现阶段，固井质量评价依靠专家人工评估，耗时耗力；同时固井质量影响因素众多，且彼此耦合作用，固井质量准确预测和固井事故地层研判的难度较大。近年来，随着人工智能技术的不断发展，图像识别、数据挖掘可实现固井质量的准确评估和预测（图6）。固井质量评价和预测主要基于声幅-变密度等测井数据，通过有监督学习算法训练模型，实现固井质量的实时评估和智能预测。

2.4.1. 固井质量评价

Deepak Kumar Voleti建立了随机森林和神经网络等机器学习算法，基于声幅、变密度测井数据和超声成像数据进行固井质量评价，最终使用集成学习方法将所有评价模型整合起来，固井质量评价准确率达99.4% [113]。Santos和Dahi使用高斯过程回归算法进行训练，根据CBL和VDL数据生成合成测井曲线，在评价水泥胶结质量方面取得了良好效果[114]。

2.4.2. 固井质量预测

Reolon等[115]通过识别声波和超声波测井数据，基于MRGC算法，计算获得水泥胶结阶段的概率，实现固井质量实时预测。Viggen等[116]使用卷积神经网络算法进行测井数据解释，输入11种测井数据进行训练，其准确率为86.7%。Viggen等[117]基于卷积神经网络预测固井水泥胶结质量和水力封隔性，其中水泥环水力封隔性的预测准确率为88.9%，固井胶结质量的预测准确率为88.5%。

2.5. 压裂智能设计与优化

智能压裂是利用人工智能和大数据技术解决压裂过程中遇到的非线性、多参数和多目标参数优化等问题。智能压裂包括压裂工艺智能设计、压裂施工过程智能监测、产能预测与压裂参数优化三个主要应用场景（图7）。

2.5.1. 压裂工艺智能设计

水平井压裂设计包括压裂位置与施工参数设计，其发展经历了多种方法和技术，从简单的解析模型到复杂的数值模型、从机理模型到目前的智能模型。利用大数据（如测井、随钻测量和岩石力学数据）和智能算法（如聚类、回归和优化算法），可实现射孔压裂工艺优化（表12 [118–123]）。目前，压裂水平井产能智能预测的精度约为70%~80%，与传统方法相比有较大提升。然而，由于数据质量和数量的限制，相关研究的现场应用实例较少。

表10 钻井风险智能预测与诊断研究现状

Application	Author	Algorithms	Input parameters	Main content
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 7-level classification of blowout risk
	Yin et al. [94]	LSTM and RNN	Includes flow difference, pool volume and WOB	A 5-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

表11 井筒稳定性智能调控研究现状

Application	Authors	Algorithms	Input parameters	Main content
Wellbore pressure	Siahaan et al. [105]	Adaptive PID	Wellhead throttle valve	Based on real-time data, not limited by prior knowledge
	Zhou et al. [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, 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

2.5.2. 压裂施工过程智能监测

压裂过程实时监测是水力压裂过程的重要环节，相较于传统手动数据特征选取与异常工况监测，人工智能技术在异常信号检测与识别上展现了显著优势。压裂过程的智能监测主要包括两个方面：压裂工况智能识别与压裂风险智能预警（表13 [78,124–130]）。

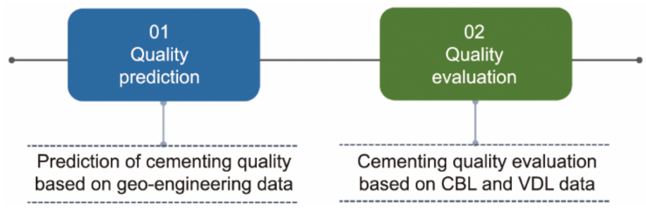

图6. 固井质量智能评价与优化。

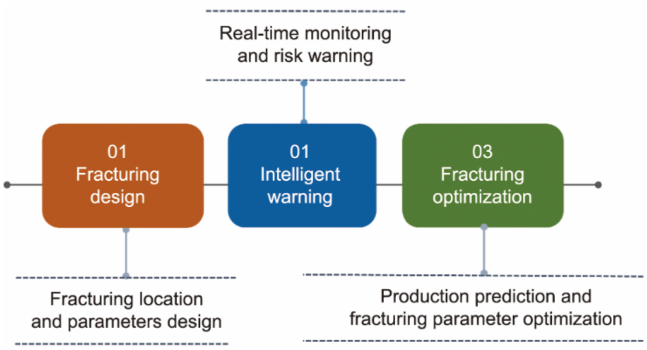

图7. 水力压裂智能设计与参数优化。

2.5.3. 产能预测与压裂参数优化

分段压裂是高效开采非常规油气资源的必要条件。压裂水平井产能预测对生产方案的评价和完井参数优化具有重要意义。随着水力压裂技术的大范围应用和人工智能的发展，将机器学习方法有效应用于参数优化设计已成为未来发展的趋势。支持向量机、决策树、神经网络及其变体等智能算法已被广泛应用于构建产能预测模型（表14 [75, 131–134]）。

2.6. 完井过程智能设计与优化

智能完井主要包含井下入流控制设备、传感器组件和地面分析系统。如图8所示，智能完井技术通过实时采集和分析井下生产状态和油藏状态等资料，以远程控制的方式进行实时监测调控从而使油井采收率最大化。在数据方面，智能完井技术的相关数据主要由静态数据和动态数据组成：静态数据包括储层性质和油井分层注采结构等，动态数据包括油井生产数据、井下传感器信息及井下控制系统参数等。在智能算法方面，通过回归算法与数值模拟相结合，预测油井产能及未来的生产动态，并使用优化算法和液压控制线来优化控制流入控制阀等井下流体控制设备的工作状态，从而实现对油井生产的实时监测、优化及调控（表15 [135–144]）。

2.7. 钻井过程全局优化与智能决策

钻井系统由地质导向、钻头破岩、管柱力学、水力学等多个子系统组成，且各子系统之间相互关联，紧密耦合（图9）。钻井工程的目标是降低钻井作业风险及成本，实现安全、高效、高质量钻进，因此需要耦合多个钻井子系统，建立集成模型来实现钻井过程的全局优化。钻井过程全局优化和智能决策是人工智能技术应用于钻完井领域的主要场景之一，对保障作业安全、缩短钻井周期、节约钻井成本意义重大。

为实现这一目标，需要将机理-数据融合的模型构建方法与钻井过程子系统耦合机制相结合，建立耦合各个钻井子系统的集成模型。该集成模型是随钻井过程动态变化的，能够为钻井过程参数优化提供基础，并且受到地面可控作业参数和钻井风险的约束，如优化后的作业参数不能引起井涌和卡钻等钻井风险。多目标优化算法和智能决策策略在钻井过程的应用必须有明确的目标，包括优化钻井速率、机械比能和钻井成本等，且算法必须具有快速、高效的特点，能够满足现场作业实时操作的要求。最后需要建立一个集成所有模型和算法的框架，以便在钻井过程中进行全局优化和智能决策。

钻井过程全局优化与智能决策关键是构建钻井子系统集成模型以优化钻井过程。虽然前人在模型构建、框架设计和系统开发等方面进行了大量研究（表16 [145–160]），但钻井过程整体优化和智能决策的研究仍处于初期阶段。

表12 压裂工艺智能设计研究现状

Authors	Algorithm	Inputs	Content and 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 net present value
Gong et al. [123]	Clustering algorithm and ANN	Rock structure and geomechanical characteristics	ANN is used to identify brittle clusters

表13 压裂施工过程智能监测研究现状

Application	Authors	Algorithm	Inputs	Content and 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, 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]	Random forest		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 machine learning 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

表14 产能预测和压裂参数优化研究现状

Application	Authors	Algorithm	Inputs	Content and Innovation
Productivity prediction	Pankaj et al. [131]	GradBoost	Includes fluid type; proppant quantity; pumping rate and BHP	Provide the best directional response in real-time
	Bhattacharya et al. [132]	RF	Includes fracturing length and casing pressure, 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, 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

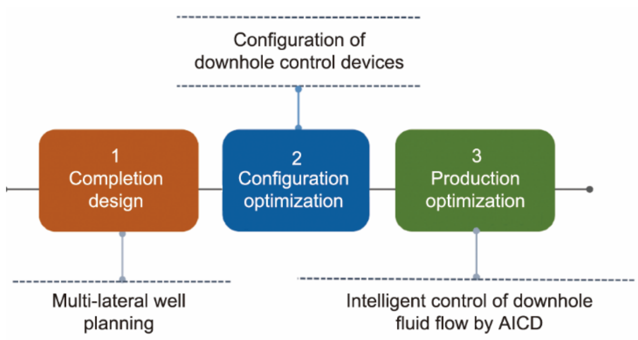

图8. 智能完井优化设计流程。

2.8. 研究现状总结

近年来，智能钻完井技术发展迅速，人工智能与油气钻完井工程的融合不断深化。油气钻完井领域的国内外学者对比研究了机器学习、深度学习等算法在不同场景下的表现和性能，并结合钻完井机理模型建立了混合模型以满足精度、效率和钻完井物理规律的需求，且机理-数据双驱动模型已成为本领域的研究热点，有望克服机理模型的局限性，提高纯数据模型的稳定性。在智能化方法落地方面，基于钻完井大数据，国内外学者的研究集中在将人工智能算法应用到地层岩性预测、钻速预测优化等钻完井场景中去，智能算法在实际钻完井过程中的应用较少。此外，当前智能钻完井算法的研究主要针对某个细分场景，还需考虑钻完井多目标、多场景动态耦合的特点研究钻完井过程全局优化。

3. 智能钻完井前景展望与挑战

近年来，智能钻完井技术发展迅速，但在数据处理、

表15 智能完井优化设计研究现状

Application	Authors	Algorithms	Input parameters	Main content
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]	Random forest	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

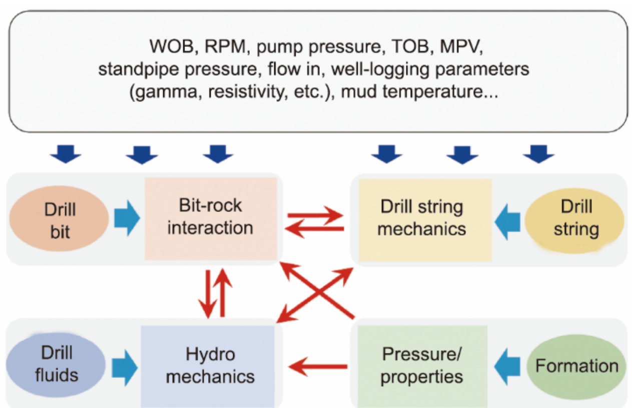

图9. 钻井过程全局优化。

智能算法、建模方法和算法落地等方面仍面临挑战，未来智能钻完井工作应重点研究上述方向（图10）。

3.1. 钻完井地质-工程大数据的标准化融合治理

钻完井大数据的标准化融合治理是智能钻完井技术发展的必要条件。钻完井数据是多源、多尺度、多类型的，包括微米级的地层孔隙结构数据和千米级的地层数据、实时监测的动态数据和地层静态数据等，其数据类型多种多样，包括数值、文本和图片等。且钻完井地质-工程大数据受井下复杂环境和数据采集装备性能的限制，存在噪声大、数据缺失等异常情况，难以满足精准表征和高效建模的需求，因此自动化、标准化的数据治理方法是油气人工智能技术落地的基础和关键。

3.2. 人工智能前沿技术应用

人工智能算法是钻完井人工智能技术的核心，其既包括广泛应用的机器学习和深度学习算法，也包括数字孪生、知识图谱、边缘计算等当前前沿智能方法。数字孪生技术具有虚实交互、实时更新、动态优化和可视化等特点，将有效提升钻完井过程风险预警和优化决策能力；知识图谱可连接不同的业务场景和对象，增强对钻完井业务网络的整体管控。边云融合计算将充分利用超级计算机等高性能计算平台与钻完井现场装备等智能终端，推动钻完井技术全过程全自主的智能化发展。

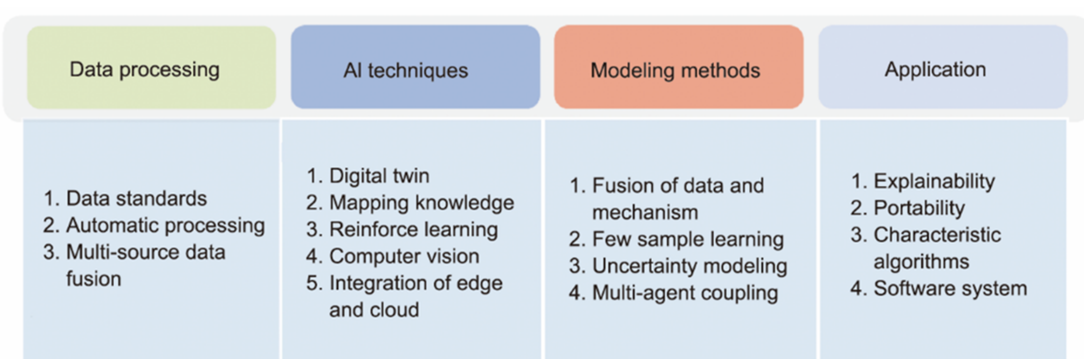

图10. 智能钻完井重点研究方向。

表16 钻井过程全局优化及智能决策研究现状

Authors/institute	Scope	Involved systems	Content/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 [156] Mayani [157] Wanasinghe [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

3.3. 结合钻完井需求建模

人工智能技术的应用需要考虑钻完井工程的实际需求。结合物理规律和专家经验等先验知识构建智能模型，可以有效提升智能模型稳定性，是推动人工智能算法落地钻完井工程的重要途径。尽管钻完井数据量巨大，但也存在标签不平衡、标签难标定、数据不可靠等难点，如溢流、卡钻等钻井风险数据，研究小样本建模方法可在有限数据条件下提高人工智能模型的性能。

3.4. 人工智能算法落地

由于钻完井工程场景多、井下环境时变性等，人工智能技术在油气钻完井领域落地面临迁移性、可解释性和实时性等难题，实际上这也是人工智能算法的共性问题。结合实际钻完井场景，探索可解释、可迁移的智能模型构建方法，形成适用于特定钻完井场景的个性化模型。此外，由于井下环境时变性的影响，基于历史数据的智能模型精度难以得到保证，攻关人工智能模型利用实时数据动态更新的方法是落地关键。

4. 结论

智能钻完井技术是实现油气开发降本增效的一项变革性技术，已成为油气行业发展的前沿技术与研究热点。本文提出了人工智能技术在钻完井领域的七个应用场景，全面回顾了各个智能化场景和技术的研究现状，并结合油气钻完井与人工智能技术的发展特点和趋势，提出了智能钻完井技术未来攻关和发展的重点方向：①研究钻完井地质-工程数据的自动化标准化融合治理方法；②加强数字孪生、知识图谱、强化学习、边缘计算等前沿技术的研究和应用；③开发机理-数据融合、小样本学习、不确定性建模等建模方法；④构建可解释、可迁移和自更新的智能模型。

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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

Abbreviation

5G	5th 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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