Sustainable Earth Resources Communications

Review

A review of stuck pipe prediction: Evolution from physical mechanism analysis to integrated intelligence

Zhonghui Li[1,2,3], Pengjie Hu[1,2,3], Xiaoliang Huang[1,2,3,*]

[1] State Key Laboratory of Low Carbon Catalysis and Carbon Dioxide Utilization, Yangtze University, Wuhan 400100, China
[2] School of Petroleum Engineering, Yangtze University, Wuhan 400100, China
[3] Western Research Institute, Yangtze University, Karamay 834000, China

* Correspondence: yangtzeuniv_huang@163.com (X.H.)

Received: February 8, 2026
Revised: March 10, 2026
Accepted: March 14, 2026
Published: March 17, 2026

Cited as:
Li, Z., Hu, P., Huang, X. A review of stuck pipe prediction: Evolution from physical mechanism analysis to integrated intelligence. Sustainable Earth Resources Communications, 2026, 2(1): 37-49.
https://doi.org/10.46690/serc.2026.01.03

Abstract: Stuck pipe is one of the most destructive downhole incidents in oil drilling operations, causing billions of dollars in losses to the global oil and gas industry each year. Current stuck pipe prediction methods face a dilemma regarding the trade-off between real-time early warning, accuracy, and interpretability. This dilemma has persisted throughout the history of prediction methods, driving a paradigm shift from empirical formulas to black-box models and ultimately to physics-aware intelligence. This paper proposes a three-dimensional adaptation framework that connects the mechanisms of stuck pipe, data frequency, and adaptive prediction methods. For example, pack-off is identified as a high-frequency, progressive type of stuck pipe, and data-driven methods are used for prediction. Based on this foundation, the paper provides a systematic review of the technical characteristics and evolutionary logic of three categories of methods: physical modeling, data-driven approaches, and hybrid fusion. Then, it provides an in-depth analysis of three major data challenges: frequency misalignment, label scarcity, and distribution skew. It discusses the paradigm shift in evaluation from statistical accuracy to engineering value. Finally, the paper looks ahead to cutting-edge directions such as digital twins, transfer learning, incremental learning, and multimodal fusion. This paper aims to provide a systematic reference for theoretical innovation and technological application in the field of stuck pipe prediction.

Keywords: Drilling; drilling safety; machine learning; stuck pipe; stuck pipe prediction

1. Introduction

Stuck pipe is a serious incident that occurs during drilling when the drill string loses its ability to move axially within the wellbore. This issue often leads to a sharp increase in non-productive time (NPT) and can result in catastrophic consequences, such as wellbore abandonment (Akpedeye, 2011; Epelle and Gerogiorgis, 2020; Hummes et al., 2012; Zhaoxuan et al., 2024). Statistics indicate that stuck pipe incidents account for 15%~25% of all NPT in drilling operations. This proportion is even higher in deepwater drilling and in complex geological environments. These incidents cause direct economic losses exceeding $5 billion annually to the global oil and gas industry (Abdali et al., 2021; Nugroho et al., 2017; Uche et al., 2025).

Traditional stuck pipe prediction relies heavily on empirical judgment and simple threshold alarms. However, these methods suffer from significant lag and subjectivity, which makes it difficult to detect early, subtle signs (Alshaikh et al., 2018; Montes et al., n.d.). As drilling depths increase and geological conditions become more complex, early warnings must provide sufficient lead time for an intervention window. However, geological uncertainties and variable operating conditions make precise forecasting challenging. Early warnings may result in a flood of false alarms, while late warnings may result in missed intervention opportunities (Montes et al., n.d.). While purely empirical formulas are easy to interpret, they are inaccurate. Conversely, purely data-driven models are accurate but difficult to interpret and trust (Xia

Yandy Scientific Press

ISSN: 3104-977X

et al., 2025; X. Zhang et al., 2024). Physics-data fusion attempts to balance these two aspects, but suffers from complex architecture and deployment challenges. Each paradigm shift represents a rebalancing of this trade-off (Fu et al., 2025; Zhang et al., 2025).

This paper proposes a three-dimensional adaptation framework to clarify the relationship between stuck pipe incident mechanisms, data frequency, and adaptation-based prediction methods. A pack-off-blockage event is a high-frequency, gradual failure characterized by the slow accumulation of cuttings over several hours and a corresponding gradual trend in standpipe pressure and torque (Kamp and Rivero, 1999; Miao et al., 2023; Zakerian et al., 2018). This requires the use of deep temporal models, such as long short-term memory (LSTM) networks and transformers, to capture long-range dependencies (Cao et al., n.d.; Graves, 2012). Differential sticking events manifest as coupled high- and low-frequency failures involving complex interactions between high-frequency signals, such as sudden changes in hook load, and low-frequency parameters, such as mud density and pore pressure (Alshaikh and Amanullah, 2018; Dupriest et al., n.d.; Outmans, 1958; Pal et al., 2000; Sampaio and Lourenco, 2013). These events necessitate the use of hybrid models to fuse multi-frequency data. Geometric sticking manifests as a low-frequency, event-based failure where design parameters, such as wellbore curvature and drill string stiffness, play a dominant role. Sudden resistance anomalies occur during tripping. This requires white-box methods, such as torque-friction models (Zhu et al., n.d.). The core insight of this framework is that model selection should depend on the match between signal frequency and failure evolution patterns rather than blindly pursuing algorithmic complexity. Although deep learning can theoretically simulate geometric sticking phenomena, field engineers often prefer statistical threshold methods for practical deployment due to their advantages of near-zero latency and interpretability.

This paper examines the development and evolution of wellbore stability prediction methods, systematically tracing the technological progression from empirical formulas to physics-based intelligent systems. Chapter 2 analyzes the frequency-layered nature of wellbore stability formation mechanisms to establish the physical basis for prediction methods. Chapter 3 elaborates on the evolutionary logic of prediction methods, from single-method approaches to integrated methods. Chapter 4 discusses three major data challenges: frequency misalignment, label scarcity, and distribution skew. Chapter 5 reviews the shift in evaluation criteria from statistical accuracy to engineering value. Chapter 6 envisions a paradigm shift from prediction to prevention. Finally, the paper concludes by summarizing the findings and distilling methodological insights for engineering artificial intelligence.

2. Types of stuck pipe and influencing factors

Sticking is not a single failure mode, but rather a manifestation of various complex downhole conditions (Hu and Yang, 2026; Wu and Ansari, 2025; Yang et al., 2026). Based on their formation mechanisms and mechanical characteristics, there are three major types of sticking: pack-off, differential, and geometric (Kharlamov and Al-obaidi, 2024; Mahmood and Assi, 2024). This chapter argues that the choice of predictive method should be determined by the frequency distribution of these types of sticking.

2.1 Type of stuck pipe

2.1.1 Pack-off

A pack-off plug is a type of stuck pipe condition in which cuttings, wellbore spalling, or solid stages of drilling fluid accumulate in the annulus, forming a plug that obstructs the normal movement of the drill string (Bailey et al., 1991; Cho et al., 2000; Qu et al., 2021; Sorgun, 2017). The formation of a pack-off plug involves a complex interplay of cuttings transport dynamics, wellbore cleaning efficiency, and the rheological properties of the drilling fluid. In horizontal and extended-reach wells, cuttings tend to form a bed at the bottom of the wellbore due to gravity. When the cuttings bed's thickness exceeds a critical value or encounters flow rate fluctuations, it may suddenly collapse and form a bridge plug (Kamp and Rivero, 1999; Miao et al., 2023; Zakerian et al., 2018). A pack-off plug evolves distinctly and progressively, typically taking several to tens of hours to develop from the gradual accumulation of a cuttings bed to a sudden blockage. During this period, parameters such as string pressure and torque exhibit a continuous upward trend (Kamp and Rivero, 1999). Analysis of data from the Volve oilfield shows that, two to four hours before a bridge block occurs, the rate of increase in string pressure can reach two to three times the normal value, and torque fluctuations can increase by more than 40%. These gradual precursors provide clear features for signal processing with deep learning methods based on time-series analysis. Long short-term memory (LSTM) networks capture long-range dependencies through gating mechanisms, and transformer models capture global correlations via self-attention mechanisms. Both are optimal choices for adapting to such high-frequency, gradual failures in scenarios with sufficient high-quality high-frequency data, on-site GPU edge devices, and single-stuck pipe mechanisms (Graves, 2012). Recent research indicates that an unsupervised anomaly detection method based on LSTM autoencoders achieved point-level 99.06% accuracy and a 94.15% F1 score on Volve oilfield data, eliminating reliance on the "stuck pipe" label. The event-level evaluation metrics for this method were 89.2% accuracy and 85.6% F1 score, which are more aligned with the engineering needs of stuck pipe prediction in drilling operations (Al-Mamoori et al., 2025).

2.1.2 Differential sticking

Differential sticking occurs when the drill string contacts a permeable formation. When the difference between the drilling fluid column pressure and the formation pore pressure exceeds a critical value, the drill string becomes adhered to the wellbore wall, resulting in adhesive sticking. This phenomenon is mechanically caused by a normal force generated by the pressure differential that presses the drill string against the wellbore wall (Alshaikh and Amanullah, 2018; Dupriest et al., n.d.; Outmans, 1958; Pal et al., 2000; Sampaio and Lourenco, 2013). The drill string loses its ability to move when the friction at the contact surface exceeds the drilling capacity of the rig. Unlike pack-off, the core sensitive variables of differential sticking exhibit a mixture of high and low frequency characteristics. High-frequency variables include abnormal drops in hook load and static fluctuations in torque. Low-frequency variables include drilling fluid density, mud cake mass, and formation pore pressure (Zhu et al., n.d.). Critically, differential sticking can occur suddenly, within minutes of the drill string coming to a standstill. Therefore, predictions must integrate real-time monitoring data with historical drilling fluid performance data to establish a dynamic assessment model of the mechanical equilibrium boundary. Purely data-driven models struggle to handle this frequency heterogeneity, and purely physical models cannot adapt to real-time operational changes. Therefore, a hybrid model is the best choice in scenarios with coupled stuck pipe mechanisms and moderate signal complexity: the physical model provides a safe operating envelope, and the data-driven model captures real-time deviations.

2.1.3 Geometric sticking

Geometric sticking occurs due to a mismatch between the wellbore trajectory and the geometric characteristics of the drill string (Zhu et al., n.d.). This phenomenon includes subtypes such as key seating sticking, dogleg sticking, and borehole diameter reduction sticking. Key seating sticking occurs in sections of the wellbore where the dogleg severity exceeds the standard. This causes the drill string joints to move back and forth within the key seating until they become stuck. Borehole-diameter-reduction sticking, on the other hand, is related to geological factors, such as shale hydration and expansion, and salt rock plastic flow. The sensitive variables associated with geometric sticking exhibit a distribution characterized by low-frequency dominance and high-frequency support. Design parameters such as wellbore curvature, drill string stiffness, and outer drill string diameter are low-frequency static variables. High-frequency dynamic variables, such as periodic torque fluctuations and abnormal tripping resistance, reflect the real-time state of geometric mismatch (Millheim and Apostal, 1981; Mitchell and Allen, 1985). Geometric sticking often occurs suddenly during tripping operations, and traditional continuous monitoring based on drilling data may overlook critical precursors.

Given the relatively well-defined physical mechanisms involved, geometric sticking is best suited for white-box or gray-box models. Torque-friction models calculate contact forces and friction distributions by discretizing drill string elements. Alerts are triggered when the predicted friction coefficient exceeds empirical thresholds or when the hook load deviates abnormally from theoretical curves. These models have the advantages of strong physical interpretability and the absence of the need for historical sticking samples. This makes them suitable for offline risk assessment during the drilling planning stage.

2.2 Data frequency stratification

High-frequency data is derived from integrated drilling logging systems, which typically sample at frequencies ranging from 1 to 10 Hz. Key parameters include string pressure, torque, hook load, rotational speed, drilling pressure, mechanical drilling rate, inlet and outlet flow rates, total hydrocarbon concentrations, and the concentrations of its components, as well as density, temperature, and electrical conductivity. The core value lies in capturing the dynamic evolution of these parameters (Ahmed et al., 2019; AitAli et al., 2023; Alshaikh et al., 2019; Duan et al., 2006). Studies indicate that changes in parameter trends during the two to six hours preceding a stuck pipe event have greater predictive value than instantaneous values (Gulsrud et al., n.d.). However, quality challenges such as sensor drift, signal noise, and non-stationarity caused by operational mode changes affect high-frequency data, necessitating robust preprocessing algorithms (Altindal et al., 2024; Wu et al., 2025).

Low-frequency data is primarily obtained through laboratory measurements and geological modeling. This includes drilling fluid properties, such as plastic viscosity, dynamic shear stress, static shear stress, fluid loss, and mud cake thickness. Other low-frequency data includes wellbore trajectory, such as wellbore inclination, azimuth, and dogleg severity (Mitchell, 1992). Low-frequency data provides a contextual reference for high-frequency data. For instance, calculating equivalent circulation density requires combining mud density with annular pressure drop. Assessing stuck pipe risk due to pressure differential necessitates integrating pore pressure with real-time hook load (Aadnoy and Looyeh, 2019).

Integrating low-frequency and high-frequency data is key to improving prediction accuracy. For example, combining mud density (low frequency) with SPP (high frequency) enables the calculation of equivalent circulating density (ECD), which can be used to evaluate the safety margin against pressure differential-induced sticking (William et al., 2021). Models that rely solely on high-frequency data can misinterpret normal operating conditions as signs of a stuck pipe (Montes et al., n.d.). Conversely, relying solely on low-frequency data hinders real-time monitoring. The optimal strategy is to establish a risk baseline framework using low-frequency data, monitor real-time deviations using high-frequency data, and align temporal and spatial scales through data assimilation techniques (Nakagawa et al., 2021; Tsuchihashi et al., 2021; William et al., 2021). Typical coupling effects include the trade-off between mud density and riser pressure. While high-density mud increases the risk of differential sticking, it also improves cuttings transport efficiency and reduces the probability of pack-off. The interplay between drilling pressure, rotation speed, and flow rate determines the balance between mechanical drilling speed and cuttings generation rate. An improper combination may lead to insufficient cleaning during rapid drilling and ultimately trigger a chain reaction, resulting in bridging (AitAli et al., 2023). Recent studies indicate that incorporating mechanism-based constraints to screen feature combinations improves the accuracy of ensemble learning models by an average of 10%, thus validating the importance of variable coupling analysis.

Based on the above analysis, this paper presents a matching matrix of three types of stuck pipe events, their frequency characteristics, and their corresponding prediction methods. The core insight of this framework is that model selection should depend on alignment between signal frequency and failure evolution patterns. Table 1 shows the adaptation of the stuck pipe type prediction method.

The key insight of this framework is that the choice of model should depend on how well the signal frequency matches the failure evolution pattern. While deep learning can theoretically simulate the geometric sticking phenomenon, statistical thresholding methods are often preferred in practice due to their near-zero latency and interpretability.

Table 1. The adaptation of the stuck pipe type prediction method.

Stuck pipe types	Core sensitive variables	Data frequency, Characteristics	Patterns of Symptom Evolution	Appropriate prediction methods	Example models	Physical basis
Pack-off	Standpipe pressure, torque, displacement, and cuttings concentration	High-frequency data dominance	Gradual evolution over several hours	Deep learning, time-series anomaly detection	LSTM autoencoder, Crossformer	Cuttings transport dynamics, annular hydraulic model
Differential sticking	Pore pressure and annular pressure drop	High- and low-frequency data hybrid	Quasi-static triggering	Hybrid models: Mechanism modeling and data-driven	Physics-constrained LSTM	Pressure differential balance equation
Geometric sticking	Wellbore curvature, dogleg severity, BHA stiffness, torque, tripping resistance	Low-frequency data-driven with high-frequency data as a supplement	Triggered instantly	Torque-friction model, decentralized intelligent model	Rigid rod torque-friction model	Drill string mechanics, wellbore clearance analysis, contact mechanics equation

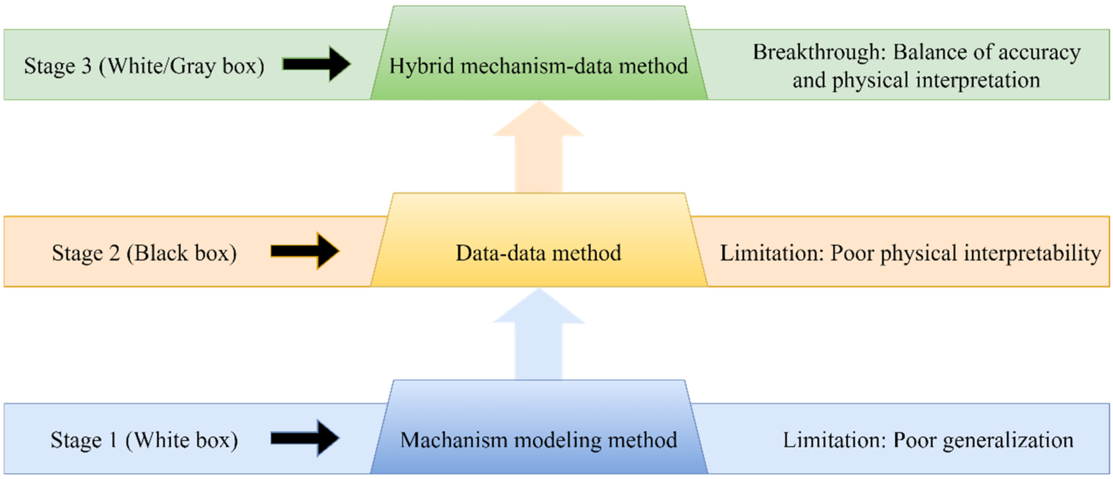

Fig. 1. Evolution of carat-diamond prediction methods.

3. Methods of predicting stuck pipe

As illustrated in Figure 1, the development of stuck pipe prediction methods can be divided into three distinct historical stages. Stage 1 involved purely physical modeling. While this approach offered white-box transparency, it suffered from poor generalization and high false alarm rates. Stage 2 saw the emergence of purely data-driven, black-box models represented by machine learning and deep learning. These models broke through the bottleneck of high-dimensional, nonlinear fitting. Stage 3 consists of physics-data fusion models, which balance predictive accuracy with physical interpretability by being driven by both data and physics. Each stage transition stems from overcoming the core shortcomings of the previous generation of methods.

3.1 Mechanism modeling method

The physical modeling stage began in the 1980s, and the torque-friction model has been a staple in predicting geometric sticking. This model divides the drill string into small segments and considers the balance of gravity, buoyancy, contact forces, and friction. It also calculates the axial resistance and torque distribution during tripping and rotation operations (Johancsik et al., 1984; Mitchell and Allen, 1985). The flexible-rod model assumes that the bending stiffness of the drill string is negligible. It uses differential equations to solve for contact forces and drag coefficients. The rigid-rod model, on the other hand, accounts for the nonlinear effects of drill string buckling and wellbore contact. This model offers higher accuracy, but it significantly increases computational complexity (Mitchell and Allen, 1985). A geometric sticking warning is triggered when the friction coefficient predicted by the model exceeds an empirical threshold or when the hook load deviates abnormally from the theoretical curve. The core advantage of such models lies in their strong physical interpretability and the absence of the need for historical sticking samples. This makes them suitable for offline risk assessment during the drilling planning stage. Hydraulic models use equations of mass and momentum conservation to calculate annular pressure drop, cuttings concentration distribution, and equivalent circulation density (Duan et al., 2006; Qu et al., 2021). A differential sticking risk is indicated when the predicted equivalent circulation density approaches the formation burst pressure or pore pressure boundary. When the cutting concentration exceeds a critical value, a bridge plug is signaled (Bailey et al., 1991). However, physical modeling has a critical weakness: parameter uncertainty. Key parameters, such as the drag coefficient and cuttings settling velocity, are influenced by complex factors, including wellbore wall roughness, cuttings shape, and drilling fluid rheology. This makes field calibration difficult (AitAli et al., 2023). Additionally, model assumptions, such as steady-state flow and homogeneous cuttings distribution, differ from actual operating conditions, resulting in cumulative prediction errors (Pearl, 2014; Shokouhi et al., 2009; Skalle et al., 2013; Zadeh, 1965). This dilemma has spurred the development of data-driven methods that allow the system to automatically learn parameters instead of relying on manual calibration.

3.2 Data-driven method

The data-driven era began in the 1980s when Hempkins et al. (Hempkins et al., 1987) developed a discriminant analysis model based on 131 well-sticking cases in the Gulf of Mexico. This model achieved a classification accuracy of 87%, pioneering data-driven well-sticking prediction (Gulsrud et al., n.d.; Hempkins et al., 1987; Wu et al., 2025). In the 21st century, algorithms such as artificial neural networks (Elkatatny, 2017; Miri et al., n.d.; Nezhad et al., 2012), support vector machines (Al-Baiyat and Heinze, 2012; Deng et al., 2024; Jahanbakhshi et al., 2012; Rostami and Khaksar Manshad, 2014), were widely adopted. Least-squares support vector machines combined with coupled simulated annealing optimization achieved high-precision classification of stuck pipe types (Chamkalani et al., n.d.). Ensemble algorithms, such as Random Forests, XGBoost, and LightGBM, which utilize Bagging or Boosting mechanisms, have effectively handled high-dimensional sparse features and noise interference (Chen and Guestrin, 2016; Hegde et al., 2015; Ke et al., 2017; Kizayev et al., 2023; Rosiani et al., 2025). These algorithms have become the mainstream choice for industrial applications. However, supervised learning faces the severe challenge of sample imbalance. Since stuck pipe events are rare in drilling history, the positive-to-negative sample ratio often exceeds 100:1. This causes models to favor the majority class (non-stuck pipe), resulting in persistently high false negative rates (Abbas et al., 2019). Research indicates that, in a dataset of 385 wells, stuck pipe samples account for only 17%, and the recall rate of traditionally trained classifiers is less than 60%.

Deep learning methods automatically extract hierarchical features from data via multiple layers of non-linear transformations, making them ideal for high-dimensional time series data. LSTM networks solve the vanishing gradient problem of traditional recurrent neural networks with a gating mechanism. This enables them to capture long-range dependencies in drilling parameters effectively (Graves, 2012). A well-sticking detection method based on LSTM networks that incorporates data augmentation and attention mechanisms improves prediction accuracy by 21.31% over baseline models (X. Zhang et al., 2024). Hybrid architectures that combine CNN and LSTM integrate spatial feature extraction with time-series modeling capabilities and demonstrate superior performance in stuck pipe prediction compared to single-architecture models (Tsuchihashi et al., 2021). Transformers and attention mechanisms represent the latest technological frontier, while the Crossformer employs dimensional partitioning embeddings and a two-stage attention mechanism to capture both temporal dependencies and cross-dimensional correlations in time series simultaneously (Liu et al., 2024). The Crossformer significantly outperforms traditional recurrent neural networks in long-sequence modeling tasks and has been successfully applied to early well-sticking detection. Training the model on normal data and using relative reconstruction error as a risk metric enabled the system to provide dynamic early warnings 30 minutes in advance. However, deep learning methods have two core challenges: a lack of interpretability and high computational resource requirements. The difficulty of tracing the decision-making process back to physical variables limits drilling engineers' confidence in the prediction results (Xia et al., 2025; X. Zhang et al., 2024). Training and inference for large-scale neural networks require GPU acceleration. Deploying these networks on edge devices presents challenges.

To address the challenges posed by the scarcity of historical stuck pipe labels and the susceptibility to labeling errors, a new approach based on unsupervised learning has been proposed (Pearl, 2014; Zadeh, 1965). An anomaly detection framework based on deep autoencoders trains the model exclusively on normal drilling data. It uses reconstruction error as an indicator of risk for stuck pipe incidents. This approach effectively avoids reliance on stuck pipe labels (LeCun et al., 2015). On the Volve oilfield dataset, this approach achieved an accuracy of 99.06% and an F1 score of 94.15%. Using only high-frequency time-series data from normal operations, this study combined gated recurrent units with deep autoencoders and optimized network weights. The output of the model, a sudden surge in reconstruction error, proved to be a highly sensitive precursor signal for stuck-pipe events (Mopuri et al., 2022). However, it must be clearly stated that this extremely high metric is based on point-level predictions. In an imbalanced engineering dataset such as that for stuck-hole drilling, where normal points typically account for over 99% of the data, point-level accuracy can be highly misleading. Even if the model correctly identifies all stuck-hole precursors as normal, it can still achieve an overall accuracy of over 99% due to the large sample size of normal data. As they lack temporal continuity and fail to account for early warning lead times, such point-level metrics cannot accurately reflect the model's value for dynamic intervention in the field.

3.3 Hybrid mechanism-data method

Purely physical models are transparent, but difficult to define in terms of parameters. Conversely, data-driven models are accurate, but their black-box properties make them difficult to interpret. This dilemma has led to the development of physics-aware artificial intelligence, which aims to balance accuracy and interpretability. The most direct approach is feature-level fusion, which utilizes the safe operating envelope provided by digital twins as input conditions for neural networks. This significantly improves the accuracy of recognizing the signs of sticking (AitAli et al., 2023). Physical-data dual-driven models incorporate physical model calculations, such as wellbore pressure, pore pressure, and collapse pressure, as well as raw drilling parameters into the neural network. This results in significantly improved evaluation metrics compared to single-data-driven models (Fu et al., 2025). A deeper level of integration involves embedding physical equations as soft constraints during neural network training. Zhang et al. (Zhang et al., 2025) proposed a Variational mode decomposition (VMD)-physical VMD and introduced gradient and power constraints after feature extraction. This ensures that the prediction results comply with the drilling power balance equation. The R^2 metric reached 0.9, significantly outperforming the unconstrained baseline model. Effectively introducing physical constraints mitigates overfitting caused by data imbalance and enhances the ability of the model to generalize under small-sample conditions (Fu et al., 2025; Zhang et al., 2025).

Physical-informative neural networks use the network's automatic differentiation capabilities to incorporate physical differential equations as soft constraints during training and calculate physical residuals (Raissi et al., 2019). Physical-informative neural networks are widely used in fluid and solid mechanics, but their direct application to predicting sticking and running is still in the exploratory stage. The primary challenge lies in the highly nonlinear nature of the physical equations that govern the drilling process and the uncertainty of their parameters. Digital twin technology represents a higher level of integration. It constructs a real-time virtual mirror image of the wellbore-drill string system and enables online comparison of theoretical mechanical parameters with actual deviations. It also dynamically locates downhole anomalies. Recent case studies indicate that real-time scenario analysis systems based on digital twins have been successfully applied in field operations. These systems automatically analyze drilling plans and have identified that up to 30% of non-productive time stems from downhole activities. This provides quantitative evidence for optimizing drilling parameters and preventive measures (Liu et al., 2026; J. Zhang et al., 2024). A digital twin system that integrates full-scale 3D wellbore trajectories, friction-torque models, and real-time data has successfully extended the lead time for stuck pipe warnings from 30 minutes to two hours (Alzahrani et al., 2022).

Credit card fraud prediction models can be classified into three categories based on their level of interpretability: white-box, black-box, and gray-box. White-box models, such as decision trees and rule-based systems, offer complete transparency regarding the relationship between inputs and outputs. However, their accuracy is limited. Black-box models, such as deep neural networks, are highly accurate, but their decision-making processes are difficult to interpret (Lundberg and Lee, 2017). Gray-box models integrate physical constraints with interpretable structures. Techniques such as Shapley values and gradient-weighted activation mapping attribute model predictions to the ranking of the importance of input features (Gomes et al., 2024). Combining LSTM networks with Shapley game theory methods allows the system to output wellbore risk curves and quantify, in real time, the marginal contribution of specific variables to the current prediction through the calculation of Shapley values at each time step. This provides drilling engineers with direct mathematical support for performing targeted troubleshooting operations (Wang et al., n.d.).

3.3.1 Application of core interpretability tools in stuck pipe prediction

Transitioning predictive models from laboratory environments to field operations requires robust interpretability frameworks. SHAP (Shapley Additive Explanations) is the most widely adopted tool for pipe blockage prediction in this context. SHAP's engineering value lies in its ability to quantify both global patterns and local, time-step-specific feature importance across diverse models, including deep learning architectures such as LSTM or Transformer and traditional machine learning algorithms like XGBoost. During practical deployment, SHAP values are integrated with LSTM-generated risk curves to evaluate the marginal contribution of critical drilling parameters (e.g., riser pressure, torque, and hook load) in real time for each prediction interval. For example, during a wellbore collapse warning event, SHAP attribution could show that the rising riser pressure rate accounts for about 65% of the predicted risk, and torque fluctuations account for about 20%. Ranking influencing factors by their computed contributions empowers engineers to quickly isolate the root cause of anomalies, such as inadequate flow rate or excessive drilling pressure, and prioritize targeted mitigation measures.

3.3.2 Engineering requirements for the application of interpretability tools

The core requirements of on-site stuck pipe prediction for interpretability tools are low latency, lightweight, and intuitive results. Therefore, the tools need to be optimized during deployment:

1) Lightweight transformation of SHAP or LIME to reduce computational load and ensure inference latency is less than one second, adapting to the needs of real-time on-site monitoring.

2) Converting interpretability results into engineering language to reduce the operational threshold for engineers.

3.4 A comprehensive comparison of stuck pipe prediction methods

To provide a quantitative comparison of the various forecasting methods, this section presents a comprehensive comparison table of forecasting methods, as shown in Table 2.

Table 2. Comprehensive comparison of forecasting methods.

Method Type	Representative Models	Applicable Datasets	Core Performance Indicators	Engineering Defects
Physical modeling	Torque-friction model, annular hydraulic model	Geological modeling dataset and low-frequency mud performance dataset	Accuracy: 75%-85% F1: 70%-80%	Difficult on-site calibration of key parameters.
Traditional machine learning	XGBoost/LightGBM, SVM/Random Forest	Labeled medium-low frequency fusion dataset, standardized logging dataset	Accuracy: 85%-90% F1: 80%-85%	1. Black-box non-interpretables 2. significant impact from sample imbalance
Deep learning	LSTM/BiLSTM auto-encoder, Crossformer/Transformer	High-frequency time-series logging dataset	Accuracy: 90%-99%, F1: 88%-94%	1.Black-box non-interpretable 2. long training cycle
Physics-data fusion	Physics-constrained LSTM/CNN, digital twin fusion model	Multi-frequency fusion dataset	Accuracy: 92%-98% F1: 88%-95%	large computational load for multi-physics coupling

4. The challenges of data and quality control

A high-quality data support system is essential for the effective performance of oil and gas exploration prediction models. However, data challenges are more than just technical details. They are strategic bottlenecks that determine the success or failure of these models. This chapter categorizes these challenges into three dimensions: frequency alignment, label scarcity, and distribution skew.

4.1 The data dilemma

4.1.1 Frequency alignment

The core challenge in predicting stuck pipe incidents is the multidimensional heterogeneity of multi-source data. In addition to the time-series monitoring data used in current mainstream research, future integration of multimodal data, such as logging images, downhole ultrasonic imaging, and unstructured drilling reports, is essential for root-cause diagnosis. However, these non-traditional data types pose significant challenges during the preprocessing stage. High-resolution logging images have extremely high feature dimensions, so efficient, real-time, high-dimensional dimensionality reduction algorithms are necessary to extract key geometric features, such as wellbore collapse patterns or keyway development. On the other hand, the depth-domain features of images, the semantic features of text, and the time-domain signals from sensors differ in terms of sampling scale and physical meaning. Achieving precise cross-modal feature alignment is a technical bottleneck in constructing a comprehensive risk assessment framework.

Specifically, there is an inherent frequency mismatch among real-time, time-based monitoring data, depth-based logging curve data, and discrete operational event records. Dynamic transitions between drilling operations, such as drilling, tripping, and circulation, further exacerbate this mismatch, resulting in non-stationary variations in data frequency. For instance, the sampling frequency of hook load data automatically increases to 10 Hz during tripping operations and drops to 5 Hz during drilling. This characteristic significantly distinguishes stuck pipe prediction from traditional time series forecasting tasks.

To address these challenges, this paper proposes an alignment framework specifically designed for drilling operations. First, the framework segments and classifies the data based on operation type. Subsequently, it performs a “time-depth” domain transformation based on the rate of penetration. Finally, an adaptive resampling strategy with mechanism constraints is adopted to balance computational efficiency while maintaining feature fidelity. Specifically, the framework maintains a sampling rate of 10 Hz during critical phases such as tripping in and out, while reducing it to 2 Hz during drilling cycles. This method first establishes a unified time reference while preserving the high-frequency resolution of the original log signals. Next, linear interpolation and physical mechanism constraints are used to upsample low-frequency logging data to 10 Hz. Finally, a “depth-time” relationship is established by mapping drilling speed, thereby converting logging parameters and geological features into strict time series, laying the foundation for subsequent multidimensional feature extraction.

4.1.2 Lack of data labels

In the field of predicting stuck pipes, label scarcity presents challenges that extend beyond class imbalance and manifest in three critical dimensions. First, actual stuck pipe events occur at an exceptionally low rate of less than 1%, significantly below the 5%-10% anomaly incidence commonly seen in general time series machine learning. Second, positive samples violate independence and identical distribution assumptions because instances within the same geological block are strongly correlated due to shared local conditions. Third, the absence of standardized engineering thresholds for identifying precursors leads to inconsistent annotations for identical data patterns due to subjective label assignment that relies heavily on personnel experience. For example, there is no consensus on how much pressure rise qualifies as a pre-stick signal. Additionally, field data lacks pure stuck pipe samples. Records invariably contain co-occurring incidents, such as wellbore leakage or blowouts, resulting in label noise rates as high as 20%. This phenomenon is seldom encountered in conventional time series tasks.

4.1.3 Data distribution skew

Existing models are usually trained for particular oil fields or blocks and lack cross-domain generalization capabilities. Significant differences in geological conditions, operational practices, and equipment types between the training and deployment data can cause a sharp decline in model performance. These challenges have driven the development of transfer learning and domain adaptation techniques. Transfer learning allows for quick adaptation in cases where there is little data by transferring knowledge between the source and target domains. Techniques such as adversarial training and domain-invariant feature learning can mitigate the mismatch between the training and deployment distributions, which is critical for predicting stuck pipe in exploration wells. Recent research combines domain adversarial adaptation with batch contrastive learning. This approach jointly optimizes label and domain classification losses to learn domain-invariant features and has achieved significant results in cross-system log anomaly detection. This methodology provides valuable insights into cross-domain transfer in drilling data.

4.2 Data quality control

4.2.1 Handling missing values and outliers

Drilling data often contains missing and anomalous values due to causes such as sensor failures, data transmission interruptions, and human recording errors. Strategies for handling missing values, such as forward or backward filling, are suitable for short-term data gaps and help maintain data continuity. Linear interpolation is appropriate for slowly changing parameters, such as well depth and temperature. Model interpolation establishes a regression model based on the correlation between adjacent parameters. For instance, it can be used to predict missing equivalent circulation density based on riser pressure and inlet flow rate (Bo et al., 2024). Outlier detection requires distinguishing between noise and true anomalies. The Isolated Forest method identifies outliers by analyzing the average path length of randomly partitioned trees, making it efficient and robust for high-dimensional data (Liu et al., 2008). However, statistical methods such as the 3σ rule and box plots are simple to calculate, yet they assume a known data distribution. This limits their applicability to the non-Gaussian characteristics of drilling data.

4.2.2 Prevent data leaks

Data leakage is a common pitfall that can lead to inflated performance estimates in machine learning models (Abbas et al., 2019). It occurs when information that was unavailable at the time of prediction is used during training. Examples of data leakage include training models with data processed after a stuck pipe incident, using well logging interpretations from the completion stage for real-time predictions during the drilling stage, and employing features from after the target time for time-series forecasting. Mitigation strategies include strict temporal partitioning, verifying feature timestamps, and using rolling validation frameworks that simulate real-time deployment (Montes et al., n.d.).

5. Shift in the evaluation of the stuck pipe prediction model

A scientific evaluation framework is essential for connecting models from research to engineering applications. However, when it comes to evaluating stuck pipe prediction, the focus should shift from statistical accuracy to engineering value. In other words, engineers care about lead time and reliability.

Traditional metrics for classification tasks include accuracy, precision, recall, and F1 score.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

$$F1 = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall} \tag{4}$$

TP (true positive) is when the model correctly predicted a stuck drill accident, which subsequently occurred. FP (false Positive) is the model that issued a warning, but the stuck drill accident did not subsequently occur. FN (false negative) is when the model did not issue a warning, but a stuck drill accident did occur (missed detection). TN (true negative) is when the model did not issue a warning, and there was no stuck drill, indicating that the system was operating normally.

In stuck pipe prediction, these metrics underperform due to data imbalance. Assuming an incidence rate of cardiac arrest of 1%, a model that consistently predicts "no stuck pipe" would have an accuracy rate of 99%, but a recall rate of 0%, rendering it useless for providing early warnings (X. Zhang et al., 2024). Therefore, recall and F1 score are more valuable than accuracy. However, traditional metrics still struggle to reflect the timeliness and consistency of early warnings. Event-level evaluation replaces point-level evaluation, treating multiple predictions within a continuous time window as a single event. A warning is deemed successful only when the proportion of positive predictions within the window exceeds a threshold. This avoids evaluation fluctuations caused by single-point anomalies (Tatbul et al., 2018). This approach better aligns with the collective nature of card-drill anomalies. Precursors to card-drill events typically manifest as sustained parameter trend anomalies lasting several hours rather than single-point mutations. To address the shortcomings of traditional evaluation metrics in failing to reflect the timeliness of early warnings, the study introduced a collective anomaly evaluation system from time-series anomaly detection. The anomaly detection benchmarks proposed by Lavin et al. (Lavin and Ahmad, 2015) and Tatbul et al. (Tatbul et al., 2018), along with the developed time-series evaluation algorithms, provide revised metrics for evaluating card-drilling predictions. These metrics assess not only whether the model successfully triggered an alarm, but also use mathematical functions to quantitatively weigh the continuity and lead time of the early warning.

The real decision-making dilemma in engineering deployment is balancing the costs of false positives and false negatives. A false positive occurs when the model incorrectly predicts a stuck pipe, resulting in unnecessary drilling stoppages for inspection and reducing operational efficiency. A false negative occurs when the model fails to predict an actual stuck pipe, resulting in accident-related losses. Of these two types of errors, false negatives are often several orders of magnitude more costly than false positives. Therefore, engineering practice typically requires models to prioritize high recall, tolerating a certain degree of false positives. Then, the false positive rate is reduced through manual review or secondary filtering. Although historical data is used to evaluate model accuracy, there is a risk of distribution bias because the geological conditions, operational practices, and equipment types in the training data may differ significantly from those in the deployment data. Consequently, cross-well validation provides a better reflection of true generalization ability than random splitting.

6. Outlook for the future

Based on the preceding analysis, this paper outlines three key areas of development in the field of stuck pipe prediction.

1. Digital twin technology creates a real-time virtual replica of the wellbore-drill string system. This provides a physically consistent simulation environment for predicting stuck pipe (Pan and Yang, 2009). Future developments will include multi-physics coupling to integrate fluid dynamics, solid mechanics, and thermodynamics models, achieving more realistic simulations of downhole environments. Another development is real-time model calibration, which employs data assimilation techniques to update the state of the digital twin continuously and reduce model bias. Third, a cloud-edge collaborative architecture balances computational efficiency with model accuracy by training complex models in the cloud and performing real-time inference at the edge.

2. Drilling geological conditions change continuously with depth, making it difficult for static models to maintain long-term accuracy. Incremental learning enables models to update continuously based on new data streams, eliminating the need for retraining on historical data (Parisi et al., 2019). Techniques such as experience replay and parameter regularization ensure that learning from new data does not undermine previously acquired knowledge.

3. In addition to traditional engineering parameters, emerging data sources provide supplementary information for predicting stuck pipe. Downhole ultrasonic imaging and borehole logging technologies can identify wellbore steps, key seatings, and constrictions in real time. These technologies provide direct, high-precision physical boundary inputs for the early warning of geometric stuck pipe incidents (Bhatia et al., 2025; Forest-Bize et al., 2022). Multimodal fusion integrates visual, temporal, and textual information to construct a more comprehensive risk assessment framework.

Drilling engineers are the end users of the stuck pipe prediction system, so the system's practical value depends on the reliability and acceptability of the model. Future research should focus on developing interpretable human-computer interfaces that effectively integrate model predictions with expert experience. At the same time, efforts should be made to prevent skill erosion and accountability issues resulting from overreliance on automation.

7. Conclusions

This paper provides a systematic review of the evolution of stuck pipe prediction methods in oil drilling, as well as the key technologies involved. It also proposes a three-dimensional adaptation framework to elucidate the relationship among stuck pipe mechanisms, data frequency, and adaptation prediction methods. The specific research conclusions and implications are as follows:

1. The paradigm shift in stuck-pipe prediction is the inevitable result of the trade-off between "accuracy, interpretability, and engineering value." Currently, the physical information fusion paradigm is the optimal choice for balancing these three factors rather than simply pursuing algorithmic complexity.

2. The core of stuck-pipe prediction lies in "domain-specificity." Its data, model adaptation, and evaluation framework must all be grounded in drilling mechanics and field conditions. It cannot simply adopt generic machine learning methods.

3. There is no "one-size-fits-all" model for stuck-pipe prediction. Model selection requires dynamic, scenario-based adaptation based on data volume, computational resources, and the degree of coupling with stuck-pipe mechanisms. When data is limited, simple models are preferable to deep learning.

4. The evaluation of stuck-pipe prediction must shift from "statistical accuracy" to "engineering value." The most critical on-site evaluation metrics are the lead time of effective early warnings and the reduction in non-productive time.

5. The future direction of wellbore sticking prediction is from prediction to prevention. The core technologies for achieving root-cause prevention are digital twins, incremental learning, and multimodal fusion, while interpretability and human-machine collaboration are key to engineering implementation.

Author Contributions

X.H.: conceptualization, methodology, software; Z.L.: data curation, writing—original draft preparation; X.H.: visualization, investigation; P.H.: supervision; P.H.: software, validation; Z.L., P.H., X.H.: writing—reviewing and editing. All authors have read and agreed to the published version of the manuscript.

Funding

This research received no external funding.

Data Availability Statement

Not applicable here.

Acknowledgments

Not applicable here.

Conflict of interest

The authors declare no conflict of interest.

Use of AI and AI-assisted Technologies

No AI tools were utilized for this paper.

Open Access

References

Aadnoy, B. S., Looyeh, R. Petroleum rock mechanics: drilling operations and well design. Gulf professional publishing, 2019.

Abbas, A. K., Flori, R., Almubarak, H., Dawood, J., Abbas, H., Alsaedi, A. Intelligent Prediction of Stuck Pipe Remediation Using Machine Learning Algorithms. Presented at the SPE Annual Technical Conference and Exhibition, SPE, Calgary, Alberta, Canada, 2019.

Abdali, M. R., Mohamadian, N., Ghorbani, H., Wood, D. A. Petroleum well blowouts as a threat to drilling operation and wellbore sustainability: causes, prevention, safety and emergency response. Journal of Construction Materials, 2021, 2652 3752.

Ahmed, O. S., Aman, B. M., Zahrani, M. A., Ajikobi, F. I. Stuck Pipe Early Warning System Utilizing Moving Window Machine Learning Approach, Presented at Abu Dhabi International Petroleum Exhibition and Conference. SPE, 2019.

AitAli, R., Arevalo, P., Dashevskiy, D., Mahmoud, M., Pocaterra, A., Al Bouny, A., Hussain, M. Q., Baruno, A., Mohammed, S. Hybrid Data Driven Intelligent Algorithm for Stuck Pipe Prevention, Presented at ADIPEC. Presented at the ADIPEC, SPE, Abu Dhabi, UAE, 2023.

Akpedeye, K. U. Advancement on Drilling Technology in Petroleum Industry, 2011.

Al-Baiyat, I., Heinze, L. Implementing Artificial Neural Networks and Support Vector Machines in Stuck Pipe Prediction, in: SPE Kuwait International Petroleum Conference and Exhibition. Presented at the SPE Kuwait International Petroleum Conference and Exhibition, SPE, Kuwait City, Kuwait, 2012.

Al-Mamoori, H. N., Tian, J., Ma, H. Stuck Pipe Detection in Oil and Gas Drilling Operations Using Deep Learning Autoencoder for Anomaly Diagnosis. Applied Sciences, 2025, 15: 5042.

Alshaikh, A., Magana-Mora, A., Gharbi, S. A., Al-Yami, A. Machine Learning for Detecting Stuck Pipe Incidents: Data Analytics and Models Evaluation, in: International Petroleum Technology Conference. Presented at the International Petroleum Technology Conference, IPTC, Beijing, China, 2019.

Alshaikh, A. A., Albassam, M. K., Al Gharbi, S. H., Al-Yami, A. S. Detection of Stuck Pipe Early Signs and the Way Toward Automation, in: Abu Dhabi International Petroleum Exhibition & Conference. Presented at the Abu Dhabi International Petroleum Exhibition & Conference, SPE, Abu Dhabi, UAE, 2018

Alshaikh, A. A., Amanullah, M. A comprehensive review of differential sticking, spotting fluids, and the current testing and evaluation methods. Presented at SPE Kingdom of Saudi Arabia Annual Technical Symposium and Exhibition. SPE, 2018.

Altindal, M. C., Nivlet, P., Tabib, M., Rasheed, A., Kristiansen, T. G., Khosravanian, R. Anomaly detection in multivariate time series of drilling data. Geoenergy Science and Engineering, 2024, 237: 212778.

Alzahrani, M., Alotaibi, B., Aman, B. Novel Stuck Pipe Troubles Prediction Model Using Reinforcement Learning, in: International Petroleum Technology Conference. Presented at the International Petroleum Technology Conference, IPTC, Riyadh, Saudi Arabia, 2022.

Bailey, L., Jomnes, T., Belaskie, J., Orban, J., Sheppard, M., Houwen, O., Jardine, S., McCann, D. Stuck pipe: causes, detection and prevention. Oilfield Review, 1991, 3(4): 13-26.

Bhatia, G., Yadav, A., Nanda, D., Goyal, D., Perumalla, S., Shinde, A., Jha, B., Upreti, D. Digitization of Daily Drilling Reports Using LLMs. Presented at the Middle East Oil, Gas and Geosciences Show (MEOS GEO), OnePetro. 2025.

Bo, C., Yu, S., Feng, X., Fukang, P. Development of Time Series Drilling Datasets for Stuck Pipe Prediction Using Volve Field Data, in: Volume 8: Offshore Geotechnics; Petroleum Technology. Presented at the ASME 2024 43rd International Conference on Ocean, Offshore and Arctic Engineering, American Society of Mechanical Engineers, Singapore, Singapore, 2024.

Cao, B., Song, Y., Yang, J., Li, L., n.d. Early signs of stuck pipe detection based on Crossformer. arXiv 2025, 2503.07440. Available online: https://arxiv.org/abs/2503.07440 (accessed on March 2026)

Chamkalani, A., Pordel Shahri, M., Poordad, S., n.d. Support Vector Machine Model: A New Methodology for Stuck Pipe Prediction. Presented at SPE Unconventional Gas Conference and Exhibition, Muscat, Oman, January 2013.

Chen, T., Guestrin, C. XGBoost: A Scalable Tree Boosting System. Presented at Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, KDD ’16. Association for Computing Machinery, New York, NY, USA, 2016.

Cho, H., Shah, S. N., Osisanya, S. O. A three-segment hydraulic model for cuttings transport in horizontal and deviated wells. Presented at SPE/CIM International Conference on Horizontal Well Technology. SPE, 2000.

Deng, S., Pan, H. -Y., Wang, H. -G., Xu, S. -K., Yan, X. -P., Li, C. -W., Peng, M. -G., Peng, H. -P., Shi, L., Cui, M., Zhao, F. A hybrid machine learning optimization algorithm for multivariable pore pressure prediction. Petroleum Science, 2024, 21: 535–550.

Duan, M., Miska, S., Yu, M., Takach, N., Ahmed, R., Zettner, C. 2006. Transport of small cuttings in extended reach drilling. Paper SPE-104192 Presented at SPE International Oil and Gas Conference and Exhibition, Beijing, China, 5–7 December 2006.

Dupriest, F. E., Jr., William, C. E., Ottesen, S. Design Methodology and Operational Practices Eliminate Differential Sticking. Presented at the IADC/SPE Drilling Conference and Exhibition, New Orleans, Louisiana, USA, February 2010.

Elkatatny, S. Real-Time Prediction of Rheological Parameters of KCl Water-Based Drilling Fluid Using Artificial Neural Networks. Arabian Journal for Science and Engineering, 2017, 42, 1655–1665.

Epelle, E. I., Gerogiorgis, D. I. A review of technological advances and open challenges for oil and gas drilling systems engineering. AIChE Journal, 2020, 66, e16842.

Forest-Bize, N., Jarrot, A., Legendre, E., Quesada, D., Le Nir, I., Shrivastava, C., Brill, T. M. Bridging the Gap Between Geologists and Drillers: LWD Ultrasonic Imaging Goes that Extra Mile. Presented at the SPWLA 63rd Annual Logging Symposium, OnePetro, 2022.

Fu, J., Liu, W., Deng, S., Zou, Y., Hao, W., Huang, P., Li, P., Liang, L. An Intelligent Prediction Model for Stuck Pipe Driven by a Hybrid of Physics and Data. Presented at the International Field Exploration and Development Conference 2024, Xi'an, China, 12–14 September 2024.

Gomes, D., Jaritz, T., Robinson, T. S., Revheim, O. E. Enhancing Stuck Pipe Risk Detection in Exploration Wells Using Machine Learning Based Tools: A Gulf of Mexico Case Study. Presented at IADC/SPE International Drilling Conference and Exhibition. Presented at the IADC/SPE International Drilling Conference and Exhibition, SPE, Galveston, Texas, USA, 5–7 March 2024.

Graves, A. Long Short-Term Memory, in Supervised Sequence Labelling with Recurrent Neural Networks, Studies in Computational Intelligence. Springer Berlin Heidelberg, Berlin, Heidelberg, pp. 37–45.

Gulsrud, T. O., Nybø, R., Bjørkevoll, K. S. Statistical Method for Detection of Poor Hole Cleaning and Stuck Pipe. Presented at SPE Offshore Europe Oil and Gas Conference and Exhibition, Aberdeen, UK, 8–11 September 2009.

Hegde, C., Wallace, S., Gray, K. Using Trees, Bagging, and Random Forests to Predict Rate of Penetration During Drilling. Presented at the SPE Middle East Intelligent Oil and Gas Conference and Exhibition, SPE, Abu Dhabi, UAE, 15–16 September 2015.

Hempkins, W. B., Kingsborough, R. H., Lohec, W. E., Nini, C. J. Multivariate Statistical Analysis of Stuck Drillpipe Situations. SPE Drilling Engineering, 1987, 2, 237–244.

Hu, Y., Yang, Y. A Comparative Study on Drag Reduction Methods for Continental Shale Drilling in the Fuxing Block, Southeastern Sichuan Basin. Reservoir Science, 2026, 2, 81–96.

Hummes, O., Bond, P., Jones, A., Symons, W., Bishop, M., Serdy, A., Pokrovsky, S., Polito, N. Using advanced drilling technology to enable well factory concept in the Marcellus shale. Paper SPE-151466 Presented at SPE/IADC Drilling Conference and Exhibition. SPE, San Diego, California, USA, 6–8 March 2012.

Jahanbakhshi, R., Keshavarzi, R., Aliyari Shoorehdeli, M., Emamzadeh, A. Intelligent Prediction of Differential Pipe Sticking by Support Vector Machine Compared With Conventional Artificial Neural Networks: An Example of Iranian Offshore Oil Fields. SPE Drill & Completion, 2012, 27, 586–595.

Johancsik, C. A., Friesen, D. B., Dawson, R. Torque and drag in directional wells-prediction and measurement. Journal of Petroleum technology, 1984, 36, 987–992.

Kamp, A. M., Rivero, M. Layer modeling for cuttings transport in highly inclined wellbores. Paper SPE-53942 Presented at SPE Latin America and Caribbean Petroleum Engineering Conference, Caracas, Venezuela, 21–23 April 1999.

Ke, G., Meng, Q., Finley, T., Wang, T., Chen, W., Ma, W., Ye, Q., Liu, T. -Y. LightGBM: A Highly Efficient Gradient Boosting Decision Tree, in: Advances in Neural Information Processing Systems. Curran Associates, Inc., New York, USA, 2017.

Kharlamov, S. N., Al-obaidi, S. S. Analysis of pipe sticking at well drilling in the South Iraqi limestone and sandstone reservoirs. Izvestiya, 2024, 335, 91–111.

Kizayev, T., Irawan, S., Khan, J. A., Khan, S. A., Cai, B., Zeb, N., Wayo, D. D. K. Factors affecting drilling incidents: Prediction of suck pipe by XGBoost model. Energy Reports, 2023, 9, 270-279.

Lavin, A., Ahmad, S. Evaluating Real-Time Anomaly Detection Algorithms–The Numenta Anomaly Benchmark. Presented at the 2015 IEEE 14th International Conference on Machine Learning and Applications (ICMLA), Miami, FL, USA, 09-11 December 2015.

LeCun, Y., Bengio, Y., Hinton, G. Deep learning. Nature, 2015, 521, 436–444.

Liu, F. T., Ting, K. M., Zhou, Z. -H. Isolation forest. Presented at 2008 Eighth Ieee International Conference on Data Mining, Pisa, Italy, 15-19 December 2008.

Liu, M., Song, X., Zhu, Z., Li, G., Xiao, H., Fu, L., Pan, T., Li, X., Yang, Y. Inertial Effect of Drill Pipe Friction Trend and Early Warning of Stuck Pipe. Paper D021S015R004 Presented at the SPE Annual Technical Conference and Exhibition, SPE, New Orleans, Louisiana, USA, 23–25 September 2024.

Liu, M. -C., Zhu, Z. -P., Song, X. -Z., Yang, Y. -L., Pan, T., Yan, Z., Zhou, D. -T. Physics-informed autoencoder with Bayesian optimization for real-time stuck pipe risk prediction. Petroleum Science, 2026, in press.

Lundberg, S. M., Lee, S. -I. A unified approach to interpreting model predictions. Advances in neural

information processing systems, 2017, 30.
Mahmood, A. T. K., Assi, A. H. A Comprehensive Review of the Pipe Sticking Mechanism in Oil Well Drilling Operations. Jcoeng, 2024, 30, 50–70.
Miao, H., Qiu, Z., Dokhani, V., Ma, Y., Zhang, D. Numerical modeling of transient cuttings transport in deviated wellbores. Geoenergy Science and Engineering, 2023, 227, 211875.
Millheim, K. K., Apostal, M. C. The effect of bottomhole assembly dynamics on the trajectory of a bit. Journal of Petroleum Technology, 1981, 33, 2323–2338.
Miri, R., Sampaio, J., Afshar, M., Lourenco, A. Development of Artificial Neural Networks To Predict Differential Pipe Sticking in Iranian Offshore Oil Fields. Presented at International Oil Conference and Exhibition in Mexico, Veracruz, Mexico, 27–30 June 2007.
Mitchell, B. Advanced oilwell drilling engineering handbook. 1992.
Mitchell, R. F., Allen, M. B. Lateral vibration: the key to BHA failure analysis. World Oil 1985, 200.
Montes, A. C., Ashok, P., van Oort, E. Review of Stuck Pipe Prediction Methods and Future Directions. Presented at SPE Annual Technical Conference and Exhibition, New Orleans, Louisiana, USA, 23–25 September 2024.
Mopuri, K. R., Bilen, H., Tsuchihashi, N., Wada, R., Inoue, T., Kusanagi, K., Nishiyama, T., Tamamura, H. Early sign detection for the stuck pipe scenarios using unsupervised deep learning. Journal of Petroleum Science and Engineering, 2022, 208, 109489.
Nakagawa, Y., Inoue, T., Bilen, H., Mopuri, K. R., Miyoshi, K., Abe, S., Wada, R., Kuroda, K., Nishi, M., Ogasawara, H. Approach for Real-Time Prediction of Pipe Stuck Risk Using a Long Short-Term Memory Autoencoder Architecture. Paper D041S112R001 Presented at the Abu Dhabi International Petroleum Exhibition & Conference, SPE, Abu Dhabi, UAE, 15–18 November 2021.
Nezhad, M. M., Ashoori, S., Hooshmand, P., Mirzaee, M. Stuck Drill Pipe Prediction with Networks Neural in Maroon Field. 2012.
Nugroho, W. A., Hermawan, S., Lazuardi, B. H., Mirza, R. Drilling problems mitigation in geothermal environment, case studies of stuck pipe and lost circulation. Paper D031S004R004 Presented at SPE Asia Pacific Oil and Gas Conference and Exhibition, SPE, Jakarta, Indonesia, 17–19 October 2017.
Outmans, H. D. Mechanics of differential pressure sticking of drill collars. Transactions of the AIME, 1958, 213, 265–274.
Pal, K., Mangla, V. K., Joshi, N. P., Tewari, P. P., Bose, U. N. A new approach solves differential sticking problems in Geleki and Ahmedabad fields. Paper SPE-63055 Presented at SPE Annual Technical Conference and Exhibition SPE, Dallas, Texas, USA, 1–4 October 2000.
Pan, S. J., Yang, Q. A survey on transfer learning. IEEE Transactions on knowledge and data engineering 2009, 22, 1345–1359.
Parisi, G. I., Kemker, R., Part, J. L., Kanan, C., Wermter, S. Continual lifelong learning with neural networks: A review. Neural Networks, 2019, 113, 54–71.
Pearl, J. Probabilistic reasoning in intelligent systems: networks of plausible inference. Elsevier 2014.
Qu, J., Sun, X., Yan, T., Chen, Y., Hu, Q. A novel prediction model for cuttings bed height in horizontal and deviated wells. Journal of Natural Gas Science and Engineering, 2021, 95, 104192.
Raissi, M., Perdikaris, P., Karniadakis, G. E. Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations. Journal of Computational physics, 2019, 378, 686–707.
Rosiani, D., Suranta, B. Y., Sofyan, A., Pradana, F. G., Putra, R. B. Machine Learning Classifies Data for Early Warning of Stuck Pipe Detection in Geothermal Drilling. International Journal on Advanced Science, Engineering & Information Technology, 2025, 15, 44-51.
Rostami, H., Khaksar Manshad, A. A New Support Vector Machine and Artificial Neural Networks for Prediction of Stuck Pipe in Drilling of Oil Fields. Journal of Energy Resources Technology, 2014, 136, 024502.
Sampaio, J. H., Lourenco, A. A hybrid Model for predicting the likelihood of differential sticking in offshore wells. Paper OTC-24462 Presented at Offshore Technology Conference Brasil, Rio de Janeiro, Brazil, 29–31 October 2013.
Shokouhi, S. V., Skalle, P., Aamodt, A., Sørmo, F. Integration of Real-time Data and Past Experiences for Reducing Operational Problems. Presented at the IPTC 2009: International Petroleum Technology Conference, European Association of Geoscientists & Engineers, December 2009.
Skalle, P., Aamodt, A., Gundersen, O. E. Detection of Symptoms for Revealing Causes Leading to Drilling Failures. SPE Drill & Completion, 2013, 28, 182–193.
Sorgun, M. A mathematical model for estimating cuttings bed thickness in horizontal and deviated wells. Ijogct, 2017, 16, 329.
Tatbul, N., Lee, T. J., Zdonik, S., Alam, M., Gottschlich, J. Precision and Recall for Time Series, in: Advances in Neural Information Processing Systems. Curran Associates, Inc., New York, USA, 2018
Tsuchihashi, N., Wada, R., Ozaki, M., Inoue, T., Mopuri, K. R., Bilen, H., Nishiyama, T., Fujita, K., Kusanagi, K. Early Stuck Pipe Sign Detection with Depth-Domain 3D Convolutional Neural Network Using Actual Drilling Data. SPE Journal 2021, 26, 551–562.
Uche, O., Christian, O., Hasib, M., Ogwal, E. Role of Drilling Fluids in Solving Drilling Challenges: A Major Focus on Plugged Drill Strings. International Journal of oil, gas and Coal Engineering, 2025, 13, 27–36.
Wang, J., Guan, Z., Liu, M., Song, X., Wang, Z. Drilling Stuck Probability Intelligent Prediction Based on LSTM Considering Local Interpretability. Presented at the 57th U.S. Rock Mechanics/Geomechanics Symposium, Atlanta, Georgia, USA, June 2023.
William, J. K. M., Gupta, P., Sangwai, J. S. Interaction of lubricants on the rheological and filtration loss properties of water-based drilling fluids. Petroleum

Science and Technology, 2021, 39, 235–248.

Wu, H., Wang, Z., Si, L., Zou, X., Gu, J., Wei, D., Tan, C. A sticking predictor construction and evaluation method for drill tools sticking prediction. Review of Scientific Instruments, 2025, 96, 015116.

Wu, J., Ansari, U. From CO$_2$ Sequestration to Hydrogen Storage: Further Utilization of Depleted Gas Reservoirs. Reservoir Science, 2025, 1, 19–35.

Xia, B., Wang, Y., Li, Q., Song, X., Zhu, Z., Liu, M., Yang, Y. Research on Stuck Pipe Prediction Based on Supervised and Unsupervised Ensemble Learning. Processes, 2025, 13, 3309.

Yang, Y., Huang, F., Kang, S. Mechanism of Penetration Rate Improvement in Hot Dry Rock Under the Coupling of Impact Load and Confining Pressure Release. Reservoir Science, 2026, 2, 52–64.

Zadeh, L. A. Fuzzy sets. Information and control, 1965, 8, 338–353.

Zakerian, A., Sarafraz, S., Tabzar, A., Hemmati, N., Shadizadeh, S. R. Numerical modeling and simulation of drilling cutting transport in horizontal wells. Journal of Petroleum Exploration and Production Technology, 2018, 8, 455–474.

Zhang, J., Wang, H., Ji, G., Zhuo, L., Zhao, Z., Liu, X., Chen, W. Digital Twin System Utilizing Hybrid Approach of Physics Model and Machine Learning for Pipe Stuck Early Identification and Warning Based on Real-Time Data. Presented at the Offshore Technology Conference Asia, OnePetro, Kuala Lumpur, Malaysia, February 2024.

Zhang, T., Xue, Y., Meng, Z., Sader, M., Zhang, W., Li, J. Drill Sticking Prediction Based on Modal Decomposition and Physical Constraint Model of Near-Bit Data. Processes 2005, 13, 1802.

Zhang, X., Dong, P., Yang, Y., Zhang, Q., Sun, Y., Song, X., Zhu, Z. Identification Method of Stuck Pipe Based on Data Augmentation and ATT-LSTM. Processes, 2024, 12, 1296.

Zhaoxuan, L., Ting, Y., Ming, W., Jun, C., Jin, L., Huan, C. The Latest Advancements in Technology for Intelligent Drilling and Completion Equipment Research. Journal of Liaoning University of Petroleum & Chemical Technology, 2024, 44, 73.

Zhu, Q., Wang, Z., Huang, J. Stuck Pipe Incidents Prediction Based On Data Analysis. Presented at SPE Gas & Oil Technology Showcase and Conference, Dubai, UAE, October 2019.