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pu liu

CCTEG Xi'an Research Institute (Group) Co., Ltd.

zujie zou

zouzujie@cctegxian.com

CCTEG Xi'an Research Institute (Group) Co., Ltd.

dong fan

CCTEG Xi'an Research Institute (Group) Co., Ltd.

binjie he

CCTEG Xi'an Research Institute (Group) Co., Ltd.

longpeng wang

CCTEG Xi'an Research Institute (Group) Co., Ltd.

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Integrated perception, decision, and control for tricone blasthole drilling: System development and field validation

Pu Liu^{1,2,3}, Zujie Zou^{3*}, Dong Fan³, Binjie He³, Longpeng Wang³

¹School of Emergency Management and Safety Engineering, China University of Mining and Technology–Beijing, Beijing, 100083, China.

²China Coal Research Institute, Beijing, 100013, China.

³CCTEG Xi'an Research Institute (Group) Co., Ltd., Xi'an, 710077, Shaanxi, China.

*Corresponding author(s). E-mail(s): zouzujie@cctegxian.com;

Abstract

Open-pit tricone blasthole drilling requires formation perception, parameter selection, actuator control, and abnormal-condition detection to operate as a coordinated closed loop. Existing rigs usually implement these functions independently, limiting information transfer and coordinated response. We developed an intelligent control system organized around perception, decision, and control. Multisource drilling data drive online formation perception, case-based operating-parameter decision making, robust setpoint tracking, and a separate safety-supervision branch for abnormal conditions. The system was evaluated through offline simulation and field trials. In a representative hard formation, the recommended parameters increased the mean penetration rate by 33.6% and reduced relative energy consumption per unit advance by 45.3%. Field tests covered 322 blastholes and 5426.7 m of drilling. Lithology-identification accuracy exceeded 85%, and 34 of 38 drill sticking events were detected (89.5%) with a mean response time of approximately 2 s. The mean penetration rate reached 35 m/h, while the mean operating time for an 18-m hole decreased by approximately 13 min, corresponding to an increase in drilling efficiency of more than 30%. These results demonstrate the feasibility of integrating formation perception, parameter decision making, tracking control, and safety intervention in field-scale tricone drilling.

Keywords: rotary blasthole drill rig, drilling process, intelligent control system, closed-loop control, engineering validation

1 Introduction

Blasthole drilling defines the geometry and quality of the holes used for charging and therefore influences fragmentation, loading efficiency, and downstream mine productivity. Rotary tricone rigs are widely used for large-diameter blastholes, but their operating state can change rapidly as the bit crosses heterogeneous formations. In conventional operation, lithology assessment, parameter selection, and abnormal-condition handling rely heavily on operator experience. Research on rotary blasthole automation has consequently emphasized continuous process monitoring and adaptive adjustment of the principal drilling parameters as prerequisites for safe and efficient autonomous operation [1]. The central challenge is not merely to automate individual actuators, but to coordinate information and actions across perception, decision making, and control throughout the drilling cycle.

Drilling-process measurements provide a practical basis for online formation perception because the feed, rotary, and penetration responses vary with rock-breaking resistance. Field studies in open-pit mines have related monitor-while-drilling data to downhole geology [2] and used modulated specific energy for automated coal-seam detection [3]. Hidden Markov models have been applied to rock classification from multivariate drilling data [4], while data from autonomous drilling systems have supported machine-learning-based material logging and chemical assaying [5]. More recent workflows have combined feature-space transformation, data augmentation, and ensemble learning for lithology identification [6], as well as friction-corrected drilling data and a smart-rig platform for real-time field identification [7]. These studies demonstrate the value of multisource drilling data, but also show that identification performance depends on signal quality, site-specific data distributions, and the separation of geological effects from equipment dynamics. A field-deployable system must therefore convert uncertain formation estimates into stable operating targets rather than treating lithology identification as an isolated output.

Safety supervision presents a related temporal-detection problem. Downhole incidents develop through coupled changes in displacement, speed, torque, and load, so alarms based on a single instantaneous threshold are vulnerable to transient fluctuations and normal operating-state transitions. Multi-time-scale feature extraction combined with a probabilistic neural network has been used to diagnose downhole incidents [8], while amplitude-change detection and dynamic time warping have been used to distinguish incidents from normal switching behaviour [9]. Convolutional networks trained with few-shot-expanded field data have been applied to drilling-risk identification [10], and an auxiliary-classifier generative adversarial network combined with a Bayesian network has been proposed for small-sample incident diagnosis and root-cause inference [11]. These studies demonstrate the potential for earlier and more reliable detection; however, their practical effectiveness ultimately depends on whether the detection results can be translated into timely and executable safety actions.

Drilling-control research has addressed uncertain bit-rock interaction through robust control, gain scheduling, sliding-mode control, and output feedback. Robust H_∞ controllers have been developed to suppress torsional vibration and weight-on-bit fluctuations under uncertain or fractured formations [12, 13]. Gain-scheduled controllers have also been applied to real-time penetration-rate optimization and

weight-on-bit regulation as operating conditions change [14, 15]. Sliding-mode designs provide disturbance rejection and robustness to parameter uncertainty [16, 17], while optimal static output feedback offers another route for suppressing drill-string torsional vibration [18]. Related mixed-sensitivity and variable-gain integrated controllers explicitly model formation-dependent uncertainty and have been evaluated using field data or field implementation [19, 20]. Despite effective control of the targeted subsystems, these studies generally do not integrate online formation perception and abnormal-condition supervision into a unified closed-loop framework.

Taken together, the literature shows substantial progress in formation perception, abnormal-condition detection, and drilling control, but these capabilities are still commonly developed and evaluated as separate functions. This separation is particularly limiting for air-assisted tricone drilling in open-pit mines, where formation estimates must update the feed and rotary setpoints, the actuators must track those setpoints despite formation-dependent uncertainty, and a safety layer must override normal control when an abnormal condition emerges. To address this system-level coordination problem, this study develops and field-validates an integrated perception–decision–control system. The system links multisource formation perception, case-based operating-parameter decision making, robust tracking control, and temporal abnormal-condition detection through an adaptive normal-drilling loop and an independent safety-supervision branch. Offline simulations evaluate parameter selection, while field tests evaluate coordinated normal operation, drill sticking intervention, and overall engineering performance.

2 System architecture

2.1 Drilling process and control requirements

Tricone drill rigs are widely used for blasthole drilling in open-pit coal mines. In this study, a ZY250E tricone drill rig is investigated, and its drilling system is shown in Fig. 1. During drilling, the feed, rotary, and circulation systems work cooperatively to achieve rock breaking. The feed system provides axial motion and pulldown force to the bit, the rotary system drives the drill rod and bit to rotate, and the circulation system uses high-pressure air for cuttings removal and bit cooling.

The feed system consists mainly of a feed motor, reducer, sprocket, and chain mechanism. The feed motor is driven by a variable-frequency drive, and its speed and torque are converted through the transmission mechanism into feed speed and pulldown force. The feed speed describes the velocity of the feed mechanism and serves as a controlled operating parameter, whereas the penetration rate describes the resulting rate of borehole advance and serves as a drilling-performance measure. The pulldown force represents the axial load on the bit. Changes in formation properties and rock-breaking resistance therefore lead to corresponding variations in feed speed, penetration rate, load, and power.

The rotary system consists of a rotary motor, reducer, and gearbox. The motor power is transmitted to the drill rod and tricone bit to overcome rock-cutting resistance and achieve rotary rock breaking. The rotary speed reflects the rotational state of the bit, whereas rotary torque and power characterize the cutting load during drilling.

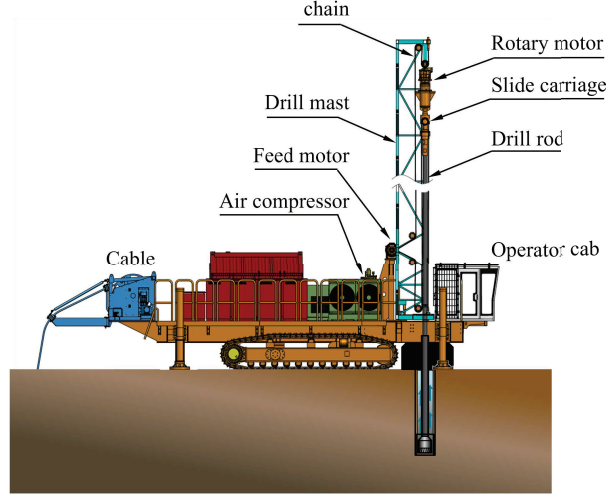


Fig. 1 Schematic diagram of the tricone rotary drill rig

The circulation system mainly consists of an air compressor and pneumatic circuit. High-pressure air is delivered through the drill rod to the bottom of the hole to remove cuttings and cool the bit. During drilling, the airflow rate remains approximately constant, while the air pressure varies with the cuttings-removal condition and airflow resistance, and can therefore provide auxiliary information on downhole drilling conditions.

During drilling, the feed and rotary operating parameters must be adjusted dynamically according to formation changes to maintain proper matching between the two systems and ensure stable and efficient drilling. The main challenge lies in coordinating perception, decision making, and control. Whether the perception results can accurately characterize the current formation and support parameter decision making, whether the decisions can be promptly translated into appropriate operating setpoints, and whether the control system can accurately execute these commands directly determine the adaptability of the drilling process to formation changes. Therefore, establishing continuous information transfer and closed-loop coordination among perception, decision making, and control is a key issue in intelligent tricone drilling control.

2.2 Intelligent control architecture

To enable adaptive adjustment of drilling parameters under varying formation conditions and safe intervention under abnormal conditions, an intelligent drilling control architecture based on a perception–decision–control framework was developed, as shown in Fig. 2. The system targets the tricone drilling process and uses multisource drilling parameters to acquire formation state, drilling state, and abnormal conditions online. Within the architecture, lithology identification uses a random forest–multilayer perceptron (RF–MLP) fusion classifier, and operating-parameter decision making uses k -nearest-neighbor (KNN) case matching. On this basis, two

coordinated control paths are established: adaptive control for normal drilling and safety intervention for abnormal conditions.

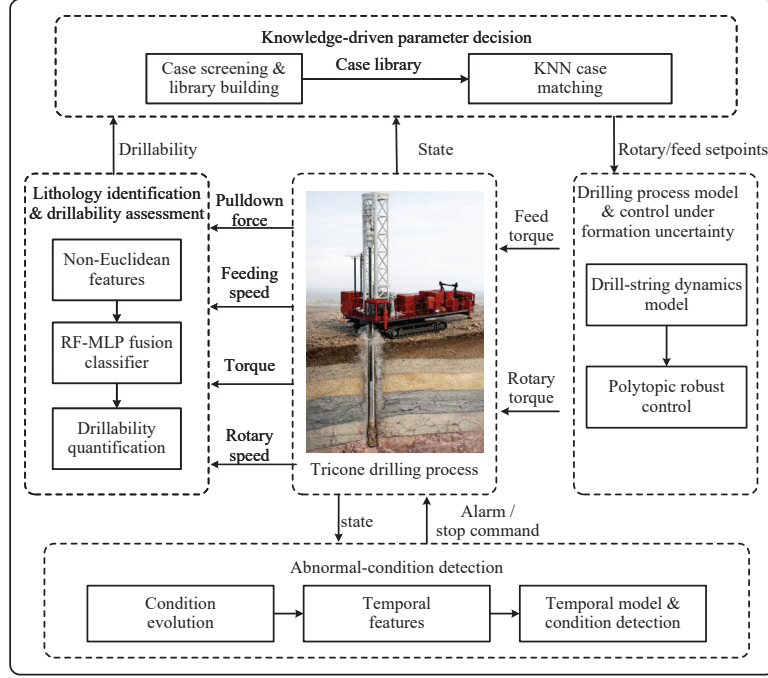


Fig. 2 Intelligent control architecture for tricone rotary drilling

During normal drilling, the formation perception module uses pulldown force, penetration rate, rotary torque, and rotary speed to identify the current lithology and quantify drillability through non-Euclidean feature construction, RF-MLP hierarchical fusion classification, and drillability evaluation. The operating-parameter decision module combines formation drillability with the real-time drilling state and retrieves matching cases from a high-quality case database to generate recommended feed speed and rotary speed. These recommended parameters are then used as control targets. To address dynamic uncertainties caused by formation hardness variations, robust control is applied to the feed and rotary systems to regulate motor torque and ensure stable tracking of the recommended feed and rotary speeds. The drilling state is subsequently fed back to the perception and decision modules, forming an adaptive closed loop of formation perception, parameter decision making, control, and state feedback.

Meanwhile, the abnormal-condition detection module operates independently of the normal parameter-control loop. It analyzes the evolution of drilling conditions from process data and detects abnormal conditions through temporal feature extraction and sequence modeling. When abnormal conditions such as drill sticking are detected,

the system issues an early warning or shutdown command to intervene in the normal drilling process, thereby forming an independent safety-supervision branch for abnormal conditions.

3 Core algorithm models and closed-loop integration

To implement the proposed intelligent drilling control architecture, dedicated algorithmic models are developed for key functions, including formation perception, operating-parameter decision making, feed control, and abnormal-condition detection. These models are further integrated according to the information flow of the overall system. This section focuses on the implementation of the core algorithms and their corresponding input–output relationships.

3.1 Formation perception

The formation perception module is designed to extract formation-related response characteristics from multisource monitoring data acquired during drilling, thereby enabling lithology identification and quantitative characterization of formation drillability. The resulting formation-state information is subsequently provided to the operating-parameter decision module. Considering the nonlinear, temporal, and strongly coupled characteristics of drilling parameters, an RF–MLP model based on non-Euclidean graph embedding is employed for lithology identification. On this basis, a continuous quantitative evaluation method for formation drillability is further introduced to jointly characterize formation properties and their drillability. The overall algorithmic framework is illustrated in Fig. 3.

For lithology identification, multisource time-series data, including feed speed, rotary speed, feed-motor torque, and rotary-motor torque, are first fed into two parallel branches for statistical feature extraction and structural feature extraction. The statistical-feature branch extracts features such as the mean, variance, and peak value to characterize the magnitude and fluctuation characteristics of the drilling parameters. In the structural-feature branch, directed visibility graphs are constructed by mapping the time-series samples into graph nodes and establishing connections between nodes according to the visibility criterion. Graph-kernel methods are then applied to extract non-Euclidean features that characterize the temporal structure and interrelationships of the drilling parameters. The statistical and structural features are subsequently fused into a comprehensive feature vector and fed into a random forest for preliminary classification. The class probabilities generated by the random forest are further input into a multilayer perceptron to obtain the final lithology classification result.

Following lithology identification, a continuous quantitative evaluation method is employed to further characterize drillability under different formation conditions. Compared with discrete lithology labels, the quantified drillability can describe continuous variations in drilling characteristics within the same lithological category, thereby providing a continuous representation of formation conditions for online adjustment of operating parameters. The algorithm operates using a 5-s sliding window, with the

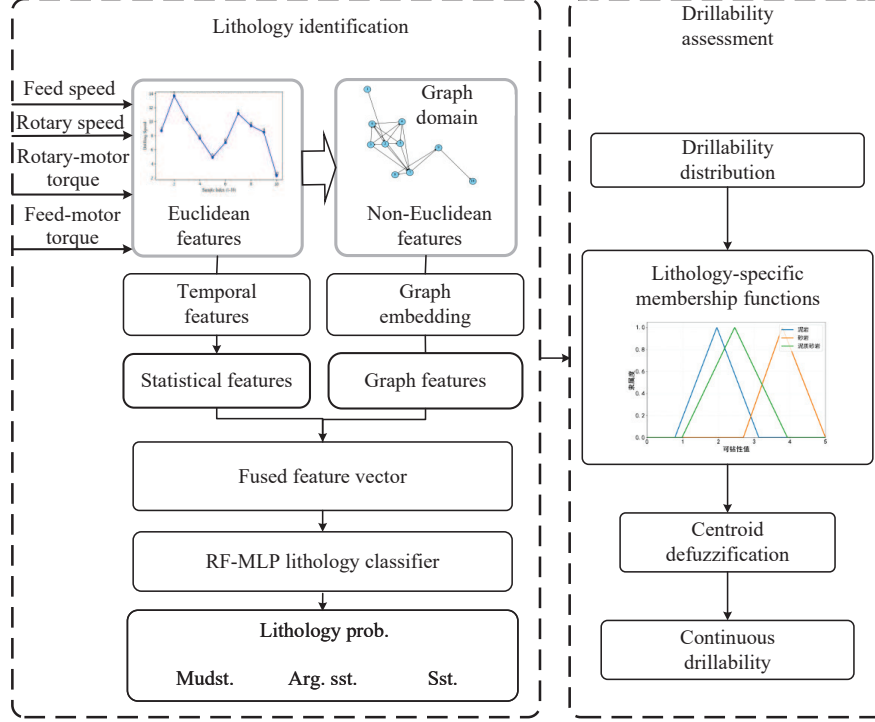


Fig. 3 Lithology identification and formation-drillability assessment framework

lithology category and formation drillability updated every 3 s. These outputs are then provided as inputs to the subsequent operating-parameter decision module.

3.2 Operating-parameter decision making

Variations in formation conditions can alter rock-breaking resistance and the load state of the drilling rig. Fixed operating parameters or manual adjustment based on operator experience cannot always ensure appropriate coordination between feed and rotary parameters, which may result in reduced drilling efficiency, increased energy consumption, and greater operational fluctuations. To address these issues, a KNN case-matching method is adopted for operating-parameter decision making. Formation drillability and the real-time operating state of the drilling rig are used as decision inputs to provide online recommendations for feed speed and rotary speed. The overall procedure is shown in Fig. 4.

The proposed method consists of two stages: offline case-base construction and online case matching. In the offline stage, high-quality historical drilling data are selected according to indicators such as drilling efficiency, energy consumption per unit advance, and operational stability. A case base is then established, containing formation drillability, drilling-rig operating states, and the corresponding operating parameters. In the online stage, the current quantified formation drillability and real-time operating state of the drilling rig are combined to form a query vector. Similar

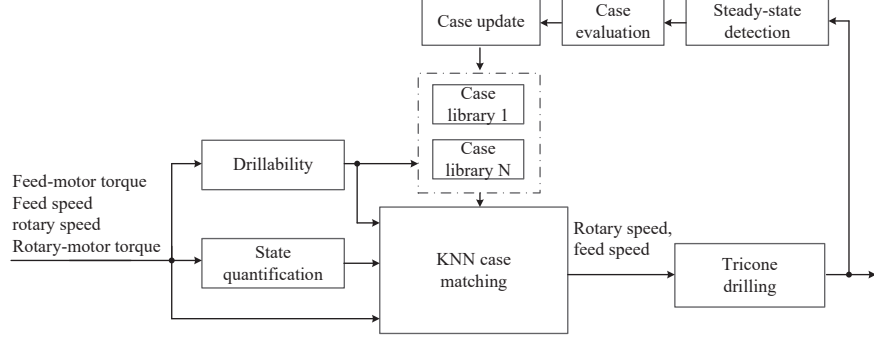


Fig. 4 Operating-parameter recommendation based on case matching

historical cases are retrieved through similarity calculation, and their corresponding operating parameters are weighted and fused to obtain the recommended feed speed and rotary speed under the current operating conditions. The recommended parameters are updated every 3 s and are subsequently used as setpoints for the drilling-parameter control system.

3.3 Drilling-parameter tracking control

The recommended operating parameters generated by the parameter decision module must be accurately implemented by the control system to achieve adaptive adjustment of drilling parameters in response to changing formation conditions. However, continuous variations in formation hardness and rock-breaking resistance during drilling can perturb the system dynamics, causing the actual drilling parameters to deviate from their recommended setpoints. To address this issue, closed-loop tracking control is employed to ensure stable implementation of the recommended parameters. The control structure is shown in Fig. 5.

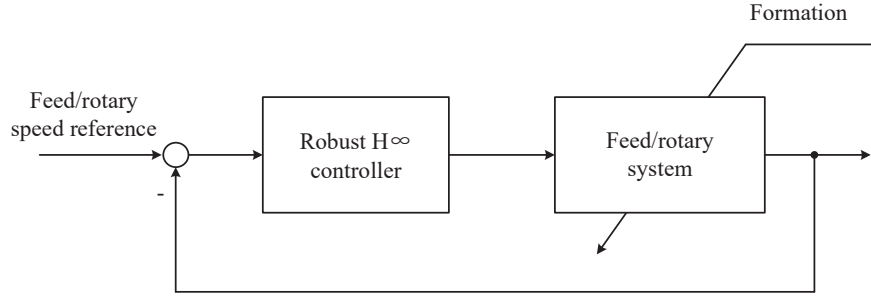


Fig. 5 Generalized closed-loop tracking-control structure for the drilling system

For the feed system, the recommended feed speed generated by the parameter decision module is used as the reference setpoint. To account for the influence of formation

hardness variations on the bit–rock interaction characteristics, a time-varying parameter representing formation hardness is introduced into the drilling dynamics model and formulated as a bounded uncertainty. By incorporating this uncertainty into the drill-string dynamics, a feed-system model with parametric uncertainty is established. Based on this model, a robust H_∞ controller is designed to regulate the feed-motor torque, enabling the actual feed speed to stably track the recommended setpoint while attenuating the effects of formation variations and external disturbances on the system dynamics.

3.4 Abnormal-condition detection and safety intervention

During drilling, factors such as abrupt local formation changes and inefficient cuttings removal may cause bit obstruction and abnormal loading. If such conditions are not detected and addressed in a timely manner, they may further develop into abnormal operating conditions such as drill sticking. Because drill sticking events are characterized by pronounced parameter changes and continuous state evolution and cannot be represented accurately by a single parameter, a temporal classification method integrating a Gaussian mixture model–hidden Markov model (GMM–HMM) and a bidirectional long short-term memory–conditional random field (BiLSTM–CRF) is adopted for online abnormal-condition detection. The overall algorithmic framework is shown in Fig. 6.

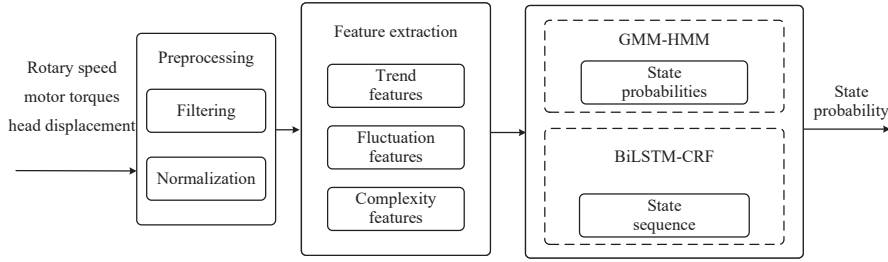


Fig. 6 Temporal-model-based abnormal-condition detection

The method takes multisource drilling parameters, including rotary-head displacement, rotary speed, feed-motor torque, and rotary-motor torque, as inputs and extracts multiscale temporal features from multiple perspectives, including trend, fluctuation, and complexity. The GMM–HMM is used to characterize the probability distributions of feature data under normal drilling and drill sticking conditions, whereas the BiLSTM–CRF captures the temporal dependencies associated with the evolution of drilling states and outputs the corresponding state probabilities. The output probabilities of the two models are then weighted and fused according to their detection performance on the validation set, yielding a comprehensive probability of drill sticking.

The algorithm operates with a 2-s sliding window and updates the classification result every 0.2 s. When the estimated probability of drill sticking exceeds the preset

threshold of 70%, the system triggers drilling-stop and alarm commands to provide safety intervention for the normal drilling control process. Offline evaluation of the detection model yielded a drill sticking detection rate of 94%, demonstrating its ability to capture temporal variations in the drilling parameters as abnormal conditions evolve. This provides a basis for real-time abnormal-condition detection and safety intervention during the drilling process.

4 Engineering validation

To evaluate the developed intelligent drilling control system and its core algorithms, simulation and field tests addressed four aspects: operating-parameter decision making, closed-loop coordination during normal drilling, safety intervention under abnormal conditions, and overall engineering performance.

4.1 Experimental platform and validation scheme

Field tests were conducted at an open-pit coal mine using a ZY250E intelligent tricone rotary drill rig as the experimental platform, as shown in Fig. 7. Both the feed and rotary systems are independently driven by electric motors. The rig has a rated drilling diameter of 200–250 mm and can acquire drilling-process parameters, including feed speed, rotary speed, and motor torque, in real time. It also supports online adjustment of operating parameters and execution of control commands. During the field tests, the minimum ambient temperature reached -25°C and the maximum wind speed was 10.8 m/s. The drilling area covered representative geological formations of the mine, providing suitable conditions for evaluating system performance in a complex field environment.



Fig. 7 ZY250E intelligent tricone rotary drill rig used in field tests

A total of 322 blastholes were completed during the experiments, and the validation procedure was organized into three stages: model training, offline simulation validation, and engineering application. Data from blastholes 1–150 were used to train and tune the lithology-identification and abnormal-condition-detection models and to construct the historical case base required for operating-parameter decision making. Data from blastholes 151–200 were used for offline simulation of the core algorithms, with particular emphasis on the recommendations generated by the case-matching method under different formation conditions. Blastholes 201–322 were used for online field validation of the overall system, focusing on the coordinated response among formation perception, parameter decision making, and tracking control during normal drilling, as well as drill sticking detection and safety intervention under abnormal conditions.

Based on the above experiments, the developed intelligent drilling system was evaluated in terms of operating-parameter decision performance, full-chain coordination under normal drilling conditions, safety intervention under abnormal operating conditions, and overall engineering performance.

4.2 Simulation validation of operating-parameter decision making

To validate the effectiveness of the case-matching-based operating-parameter decision method, drilling data obtained from a representative hard formation were selected for offline simulation. Manually specified operating parameters used in field operations were taken as the baseline, and the drilling process under the algorithm-recommended parameters was comparatively analyzed. The selected formation exhibited relatively high rock-breaking resistance and was therefore prone to high drilling loads and energy consumption. Its formation drillability values were mainly distributed between 2.3 and 2.6. Penetration rate, relative energy consumption per unit advance, and a comprehensive performance index were selected as evaluation metrics to assess the effects of different parameter-setting strategies on drilling efficiency and energy consumption.

Figure 8 compares the drilling processes obtained using the algorithm-recommended and manually specified parameters. Overall, the feed speed recommended by the algorithm was higher than that under manual operation, whereas neither feed-motor torque nor rotary-motor torque increased substantially. Thus, the efficiency improvement was attributable primarily to better coordination between feed speed and rotary speed rather than simply to increased power output. Between sample indices 50 and 190, the operator reduced feed speed without a corresponding rotary-speed adjustment, resulting in pronounced fluctuations in penetration rate and rotary load. In contrast, the algorithm increased rotary speed while maintaining a relatively stable feed speed, thereby improving parameter coordination and maintaining relatively low motor loads. Between sample indices 1230 and 1460, manual operation relied mainly on increasing feed speed, while the rotary-speed adjustment was insufficient, leading to larger process fluctuations. The proposed algorithm instead coordinated the recommended feed and rotary speeds according to the current operating conditions, resulting in a more stable drilling process.

Figure 9 further compares the performance indicators obtained using the two parameter-setting strategies. With the algorithm-recommended parameters, the mean

penetration rate reached 13.4 mm/s, compared with 10 mm/s under manual operation, corresponding to a 33.6% improvement. The mean relative energy consumption per unit advance decreased from 2.365 to 1.29, a reduction of 45.3%. Meanwhile, the comprehensive performance index increased from 0.3671 to 0.4967, an improvement of 35.3%. These results show that the case-matching method can coordinate the feed and rotary parameters according to the formation condition and real-time operating state. It therefore improves penetration performance while reducing energy consumption per unit advance and provides suitable setpoints for online control.

4.3 Full-chain coordination under normal drilling conditions

To validate coordinated operation among formation perception, operating-parameter decision making, and tracking control under normal drilling conditions, representative intervals with typical formation variations were selected from the online field data for blastholes 201–322. The corresponding results are shown in Fig. 10.

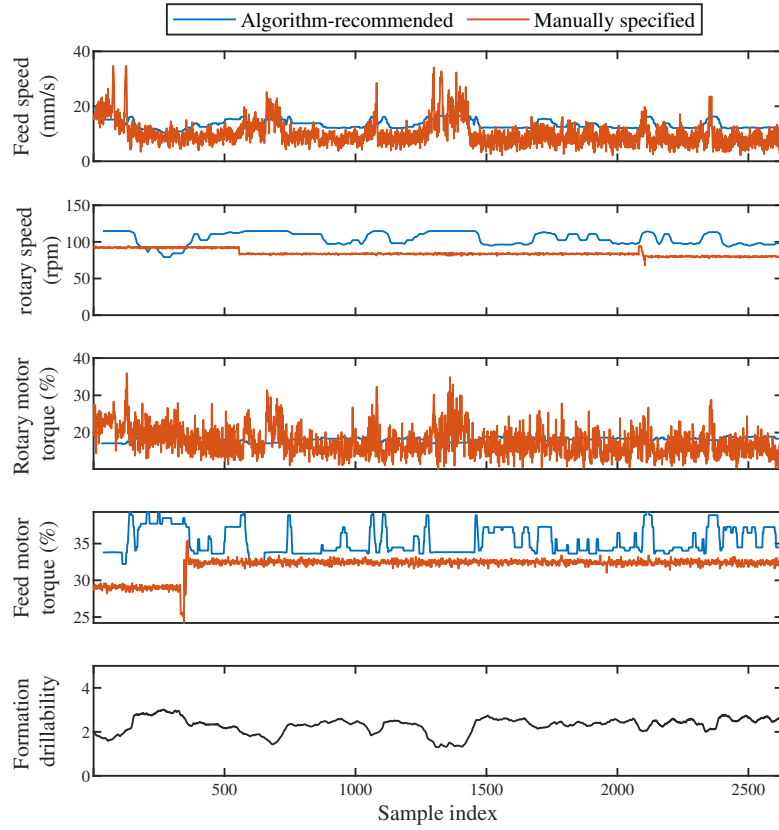


Fig. 8 Drilling-process optimization based on case matching under hard-formation conditions

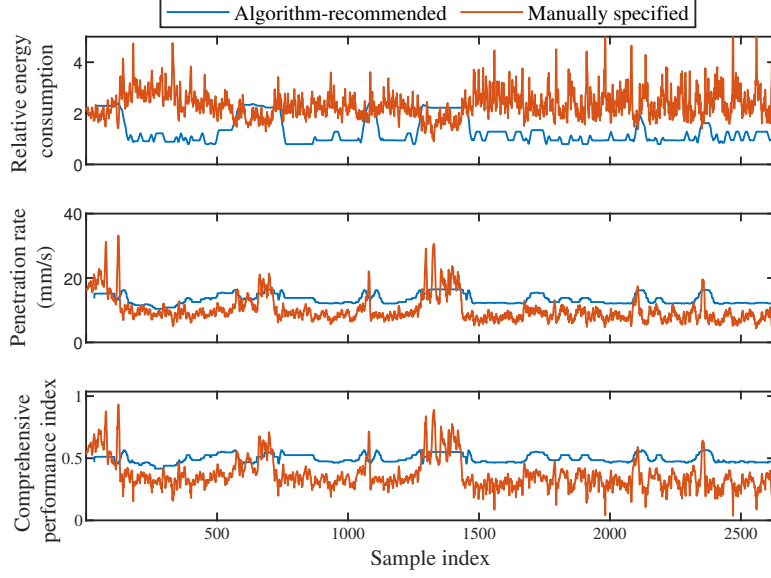


Fig. 9 Comparison of performance indicators under hard-formation conditions

During 0–20 s, the mean formation drillability was approximately 2.4 and remained generally stable. During 20–30 s, the drill rig entered a locally varying formation, and drillability decreased to approximately 1.38. At the same time, the discharged cuttings changed from gray to black. During 50–70 s, drillability increased again to approximately 2.4, while the cuttings returned from black to gray. The variation in formation drillability was therefore consistent with the observed field characteristics, indicating that the formation-perception module can characterize formation-state variations online.

As formation drillability changed, the operating-parameter decision module synchronously adjusted the recommended parameters. During 20–30 s, the recommended feed speed increased from 13.7 to 16.5 mm/s, while the recommended rotary speed increased from 94 to 115 r/min. After the formation condition recovered during 50–70 s, the recommended feed and rotary speeds were adjusted to approximately 13 mm/s and 94 r/min, respectively. Where the formation condition remained stable, the recommended parameters also remained nearly constant. These results indicate that the decision module can dynamically coordinate feed and rotary parameters according to changes in formation conditions.

The feed system uses the recommended feed speed as its control setpoint and regulates feed-motor output through closed-loop control. The rotary system responds correspondingly to the recommended rotary speed. As shown in Fig. 10, after the formation condition changed, the actual feed and rotary speeds responded rapidly and remained close to their respective recommended values, while the feed- and rotary-motor torques varied smoothly. These results demonstrate a continuous response from formation-state perception and online decision making to drilling-parameter execution,

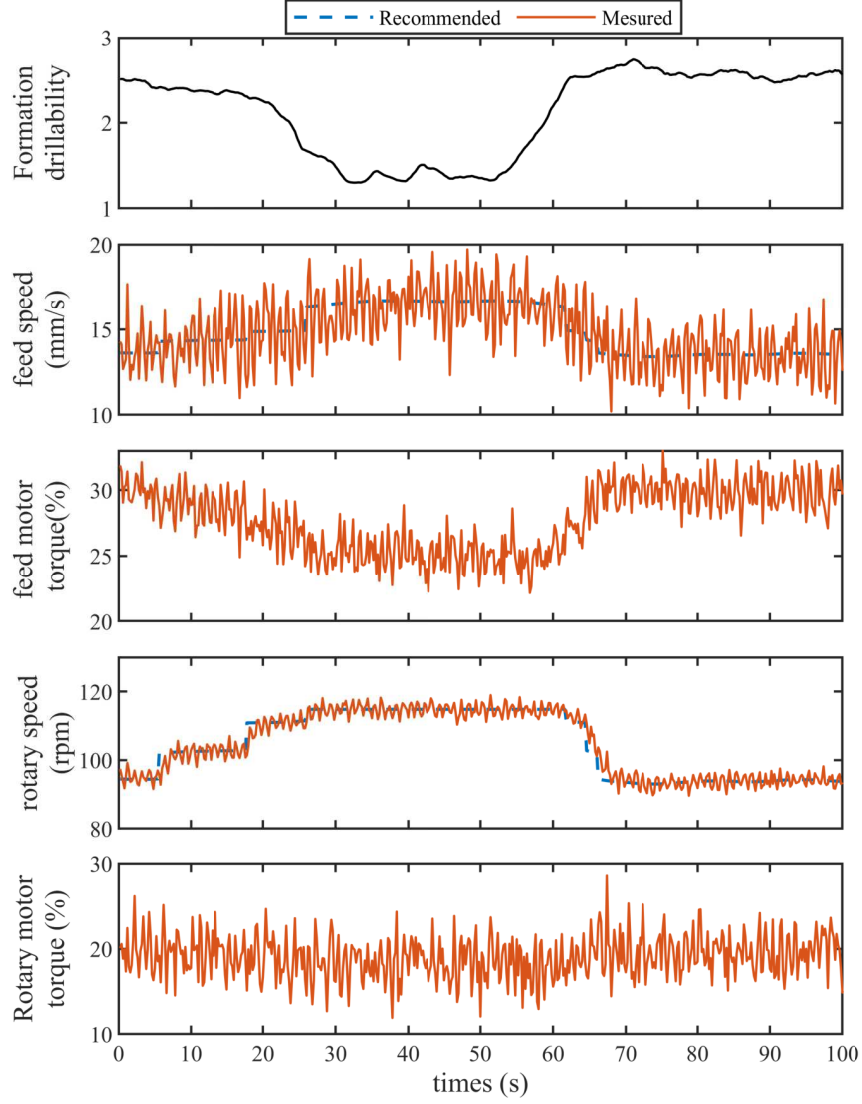


Fig. 10 Coordinated perception, decision making, and control under changing formation conditions

thereby realizing coordinated full-chain operation of the perception–decision–control framework under normal drilling conditions.

4.4 Abnormal-condition detection and safety intervention

To validate abnormal-condition detection and safety intervention, a representative drill sticking event recorded during field drilling was selected for analysis. Variations in the key drilling parameters and drill sticking probability are shown in Fig. 11. Based on historical drill sticking data, the decision threshold was set to 70%. When

the estimated probability exceeded this threshold, the system triggered drilling-stop and alarm commands.

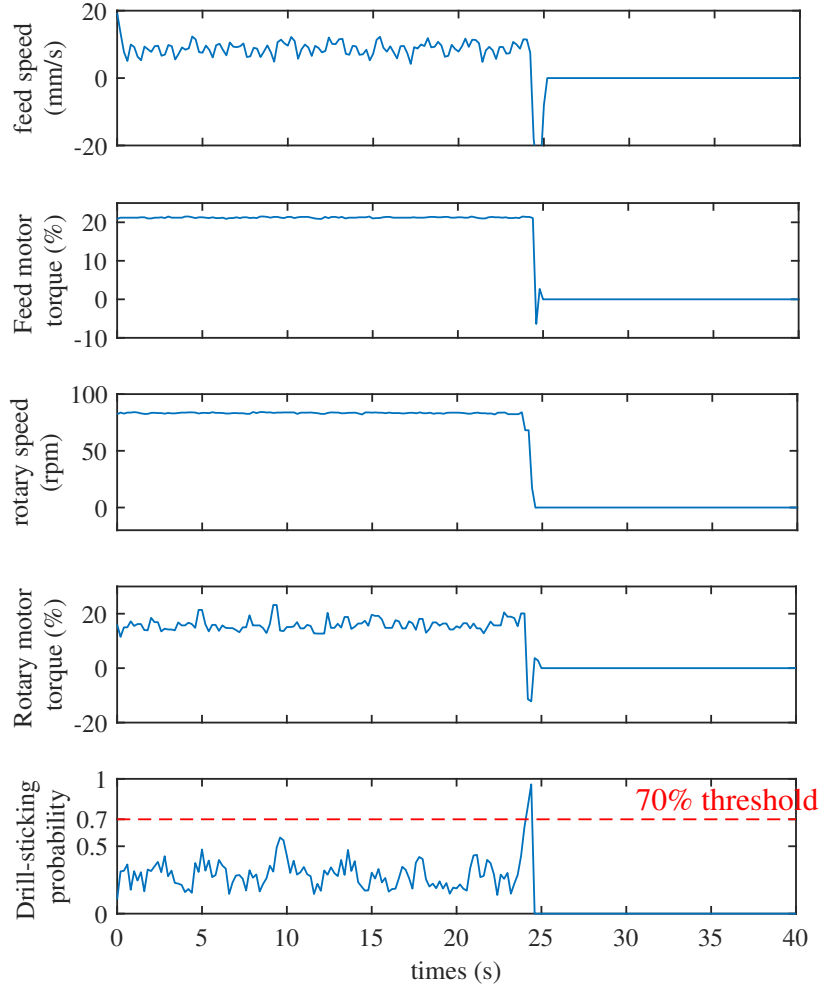


Fig. 11 Operating results during drill sticking

During 0–24 s, the drill rig remained in a normal state. Feed and rotary speeds were generally stable, while the feed- and rotary-motor torques exhibited only minor fluctuations. The drill sticking probability remained below the decision threshold. During 24–26 s, pronounced abnormal variations appeared: the feed speed decreased rapidly, rotary speed declined substantially, and motor-torque fluctuations intensified,

indicating a marked increase in bit resistance. As these characteristics persisted, the drill sticking probability rose rapidly above the 70% threshold, indicating a transition to drill sticking.

Once the drill sticking probability exceeded the threshold, the system immediately triggered drilling-stop and alarm commands. After 26 s, both feed and rotary speeds rapidly decreased to zero, accompanied by corresponding reductions in the motor torques. The drill sticking probability also decreased rapidly after drilling stopped. These results demonstrate that the abnormal-condition detection module can detect drill sticking events from temporal variations in multisource drilling parameters and promptly initiate an intervention. This establishes a closed-loop response linking abnormal-condition detection to safety intervention and verifies the engineering feasibility of the independent safety-supervision branch.

4.5 Overall system performance

Field trials were conducted from November 2025 to March 2026. Across 322 blast-holes, the cumulative drilling length was 5426.7 m. The remote response time remained below 200 ms and data-transmission packet loss did not exceed 1%, satisfying the communication requirements for online perception, decision making, and control.

Lithology-identification accuracy exceeded 85%. Of 38 drill sticking events, 34 were detected, giving a field detection rate of 89.5% and a mean response time of approximately 2 s. The mean penetration rate was 35 m/h, above the rig’s design value of 30 m/h; mean penetration rates were approximately 25 m/h in hard rock and 40 m/h in soft rock. For a typical 18-m hole, the mean operating time decreased by approximately 13 min and drilling efficiency increased by more than 30%. Hole-diameter deviation remained within ± 3 mm, depth deviation did not exceed 1%, and mean hole depth was 18.1 m.

Together, these results show that the developed system can integrate online formation perception, dynamic operating-parameter adjustment, parameter tracking, and safety intervention during field drilling. The validation was nevertheless limited to one mine and the ZY250E rig. Performance may vary with the available field data, formation conditions, and equipment characteristics. Application at another mine would therefore require retraining or recalibration of the perception and decision models using site-specific data; deployment on different equipment would also require renewed system identification and control-parameter tuning. Cross-site and cross-platform generalization should be evaluated in future work.

5 Conclusion

This study developed and field-tested an intelligent control system to integrate perception, decision making, control, and abnormal-condition detection during air-assisted tricone rotary drilling. The main conclusions are as follows.

(1) A process-wide perception–decision–control framework was established. It combines formation perception, operating-parameter decision making, tracking control, and safety intervention through a normal-drilling adaptive loop and an independent abnormal-condition supervision branch.

- (2) Under normal drilling conditions, the system adjusted feed and rotary parameters in response to formation changes and tracked the recommended setpoints. In a representative hard-formation simulation, the mean penetration rate increased by 33.6% relative to manual operation, while relative energy consumption per unit advance decreased by 45.3%.
- (3) Under abnormal conditions, the system detected drill sticking events and triggered drilling-stop and alarm commands. It detected 34 of 38 field events (89.5%) with a mean response time of approximately 2 s, demonstrating the feasibility of real-time safety supervision under the tested field conditions.
- (4) Field validation across 322 blastholes and 5426.7 m of drilling yielded a mean penetration rate of 35 m/h. For a typical 18-m hole, operating time decreased by approximately 13 min and drilling efficiency increased by more than 30%, while hole-diameter and depth deviations remained within ± 3 mm and 1%, respectively.

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