The Evolutionary Path of Dynamic Identification Algorithms for Safety Risks in Deep Coal Mines Based on Measurement While Drilling

Biao Fu
College of Energy and Mining Engineering, Shandong University of Science and Technology, Qingdao, China

Abstract: With the increasing depth of coal mining, the high ground stress, high gas pressure, and complex geological conditions faced by deep coal mines significantly increase safety risks such as rockbursts and coal and gas outbursts. Dynamic identification while drilling (DWD) technology has become an important means to achieve real-time perception and early warning of safety risks in coal and rock masses. This paper systematically reviews the evolution path of DWD dynamic identification algorithms for safety risks in deep coal mines. First, it elucidates the disaster-causing mechanism of safety risks in deep coal mines, the data acquisition and signal characteristics during drilling, and the mathematical model of the dynamic identification algorithm. Based on this, it focuses on analyzing the evolution of the algorithm from the traditional threshold algorithm stage to the machine learning algorithm stage, and then to the deep learning fusion algorithm stage. Traditional thresholding algorithms primarily rely on empirical thresholds and statistical properties to identify drilling parameter anomalies, offering advantages such as simple structure and strong real-time performance. Machine learning algorithms, employing methods like Support Vector Machines and Extreme Learning Machines, significantly enhance nonlinear feature extraction capabilities and model adaptability through data-driven modeling. Deep learning fusion algorithms utilize convolutional neural networks, long short-term memory networks, and multi-source data fusion architectures to achieve end-to-end automatic feature extraction and intelligent risk classification and prediction, effectively improving identification accuracy and robustness in complex deep environments. This paper's systematic study of the evolution path of dynamic identification algorithms during drilling provides a theoretical framework and technical support for dynamic identification of safety risks in deep coal mines.

Keywords: Deep Coal Mine; Safety Risks; Dynamic Identification While Drilling; Algorithm Evolution Path; Deep Learning Fusion

1. Introduction

1.1 Research Background and Significance

With the increasing depth of coal mining in my country, deep coal mines face increased ground stress, more complex coal and rock mass structures, and significantly enhanced multi-field coupling effects, leading to a sharp increase in the risk of dynamic disasters such as rockburst and coal and gas outburst. Traditional static risk assessment methods are difficult to meet the needs of real-time dynamic monitoring [1]. Drilling dynamic identification technology can dynamically capture the stress state and geological anomalies of coal and rock mass by collecting multi-source parameters such as torque, drilling pressure, vibration and acoustic emission in real time during the drilling process, providing direct data support for early warning of safety risks [2].

This study systematically reviews the evolution path of dynamic identification algorithms for safety risks in deep coal mines during drilling. It not only helps to reveal the inherent laws of the transformation from traditional threshold methods to intelligent fusion algorithms, but also provides theoretical basis and technical reference for improving the inherent safety level of coal mines and promoting the construction of intelligent mines, which has important engineering application value.

1.2 Current Status of Research at Home and Abroad

Domestic and foreign scholars have carried out continuous exploration around the dynamic identification technology while drilling. Early studies mainly used traditional threshold and statistical methods to identify drilling parameter anomalies by setting empirical thresholds, but due to limitations in adaptability and accuracy, they were difficult to cope with complex geological conditions in deep areas [3]. With the introduction of machine learning technology, algorithms such as support vector machine and fuzzy clustering have been gradually applied to lithology identification and risk prediction, which has significantly improved the identification efficiency.

In recent years, deep learning and multi-source data fusion algorithms have become research hotspots. Domestic and foreign scholars have proposed an intelligent perception architecture based on edge-cloud collaboration and used methods such as optimized extreme learning machine to realize real-time dynamic identification of drilling conditions. Domestic research focuses on engineering practice and has formed a hierarchical and accurate identification system of "advanced detection-real-time monitoring-drilling verification" [4]; international research focuses on the generalization ability and real-time optimization of algorithms. Although significant progress has been made, existing methods still have shortcomings in terms of robustness, interpretability and multi-parameter fusion accuracy in deep high-stress environments, and it is urgent to further clarify the algorithm evolution path and optimization direction.

2. Fundamentals of Dynamic Identification Technology While Drilling

2.1 Mechanism of Safety Risks in Deep Coal Mines

As the mining depth of coal resources continues to increase, the coal and rock mass in deep coal mines is in a complex environment of high ground stress, high gas pressure and high ground temperature. The vertical ground stress often exceeds 25 MPa, which leads to a significant increase in the instability of the coal and rock mass structure and the energy accumulation and release process, and a sharp increase in the risk of dynamic disasters such as rockburst and coal and gas outburst [5]. Its disaster mechanism can be essentially summarized as a chain process of energy-driven-damage accumulation-instability criterion (Figure 1), involving the multi-scale evolution and cross-scale linkage mechanism of mining-induced overburden structure.

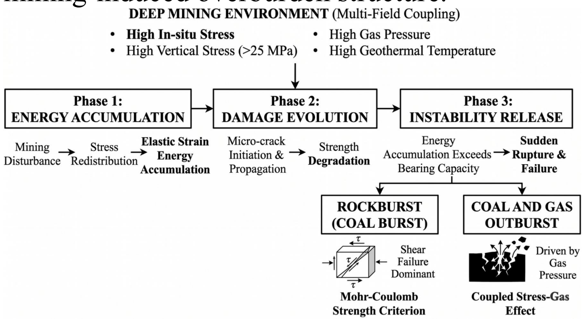

Figure 1. Schematic Diagram of the Disaster-causing Mechanism of Safety Risks in Deep Coal Mines

The failure process of coal and rock mass can be quantitatively described using the classic Mohr-Coulomb strength criterion, which is widely used in the analysis of shear failure under deep high stress conditions.

$$\tau=c+\sigma\tan\phi \tag{1}$$

Where τ represents shear strength, c represents cohesion, σ represents normal stress, and ϕ represents internal friction angle. This formula can effectively reflect the failure conditions of coal and rock mass under complex stress state and is an important theoretical basis for assessing the risk of dynamic disasters in deep coal mines [6].

Furthermore, the elastic energy index is a key indicator for evaluating the impact tendency of rocks. It is defined as the ratio of the elastic strain energy accumulated by the rock before it reaches its peak strength to the plastic energy dissipated during unloading. The calculation formula is as follows:

$$W_{et}=\frac{\phi_{sp}}{\phi_{st}} \tag{2}$$

In the formula, ϕ_{sp} represents elastic strain energy, and ϕ_{st} represents dissipated strain energy. A larger W_{et} value indicates a stronger ability of the rock to store elasticity, and a higher probability of rockburst or rock burst. The above mechanism analysis provides solid theoretical support for dynamic identification technology while drilling and guides the construction of subsequent algorithm models.

2.2 Drilling Data Acquisition and Signal Characteristics

Monitoring while drilling technology collects multi-source parameters such as drilling pressure, torque, drilling speed, rotation speed and vibration signals in real time during the drilling process to realize dynamic perception of geological anomalies in coal and rock masses. The signal characteristics of these parameters directly reflect the changes in rock drillability and safety risk status, and are the basic input of dynamic identification algorithms [7]. Mechanical specific energy (MSE) is the core indicator for evaluating drilling efficiency and rock drillability. Its physical meaning is the work required to excavate a unit volume of rock per unit time. The calculation formula is as follows:

$$E_{MSE}=\frac{4F}{\pi d^2}+\frac{480nT}{vd^2} \quad (3)$$

Where E_{MSE} is the mechanical specific energy (GPa), F is the drilling pressure (kN), d is the drill bit diameter (mm), n is the rotational speed (r/min), T is the torque (kN·m), and v is the drilling speed (m/h).

For vibration signal feature extraction, the root mean square (RMS) value is an important parameter characterizing signal intensity, and it is defined as:

$$x_{RMS}=\sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2} \quad (4)$$

In the formula, x_i is the signal value of the sampling point, and N is the total number of sampling points. The RMS value can sensitively reflect the dynamic changes in the degree of coal and rock mass fracturing during drilling, and provide reliable signal feature support for subsequent risk assessment [8]. Through the above parameter collection and feature analysis, the real-time perception capability of safety risks in deep coal mines can be significantly improved, as shown in Figure 2.

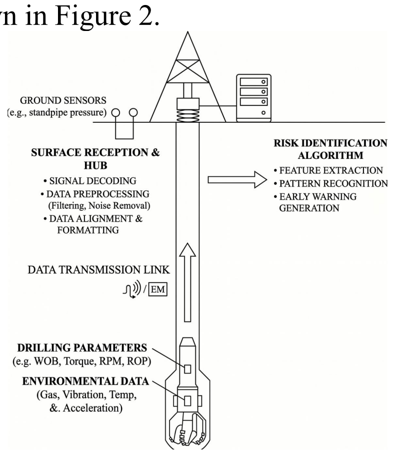

Figure 2. Schematic Diagram of the Data Acquisition System While Drilling in Deep Coal Mines

2.3 Mathematical Model of Dynamic Recognition Algorithm

The mathematical model of the dynamic identification algorithm is the core of realizing real-time assessment of safety risks in deep coal mines. It evolves from traditional threshold methods to intelligent fusion through multi-source drilling data processing and anomaly detection. Traditional dynamic identification often uses the Cumulative Sum (CUSUM) control chart method to detect parameter drift. This method has high sensitivity to process mean shifts, and its Cumulative Sum statistic is defined as:

$$S_i^{+}=\max\left(0,S_{i-1}^{+}+x_i-\mu_0-k\right) \quad (5)$$

Where $S_0^{+}=0$, μ_0 is the process mean, and k is the reference value. When S_i^{+} exceeds the decision threshold H, an anomaly is determined to have occurred. This model is suitable for detecting abrupt changes in drilling parameters.

Furthermore, the Bayesian update method can achieve real-time inference of risk probabilities, and its posterior probability formula is:

$$P(\theta \mid x)\propto P(x \mid \theta)P(\theta) \quad (6)$$

In the formula, θ represents the parameter to be estimated, and x represents the observed data. This formula, through the combination of prior knowledge and the likelihood function, enables adaptive updating of the parameters of the dynamic identification model, improving its robustness and accuracy under complex geological conditions.

3. Evolution Path of Dynamic Identification Algorithm While Drilling

The evolution path of the dynamic identification algorithm for safety risks in deep coal mines during drilling is shown in Figure 3: The first stage is to use fixed statistical thresholds to judge rule-based risk identification based on real-time drilling parameters; the second stage utilizes multivariate drilling data and achieves dynamic risk classification through feature engineering and adaptive models such as support vector machines and extreme learning machines; the third stage relies on heterogeneous multi-source data streams and adopts end-to-end intelligent prediction models such as convolutional neural networks and long short-term memory networks to achieve predictive real-time risk intelligence.

3.1 Traditional Threshold Algorithm Stage

The traditional threshold algorithm stage represents the initial development period of dynamic risk assessment (VFA) technology during drilling. It primarily relies on statistical analysis and empirically set fixed thresholds to identify anomalies in parameters such as drill pressure, torque, drill speed, and vibration signals during the drilling process. This stage of the algorithm is suitable for early-stage shallow or medium-depth coal mines with relatively stable geological conditions. It provides preliminary risk warnings by simply comparing real-time parameters with preset benchmark values, offering advantages such as ease of calculation and strong real-time performance. However, in deep, high-stress environments, its adaptability is insufficient, and it is susceptible to noise interference, leading to misjudgments or missed detections. The identification accuracy typically struggles to exceed 75%.

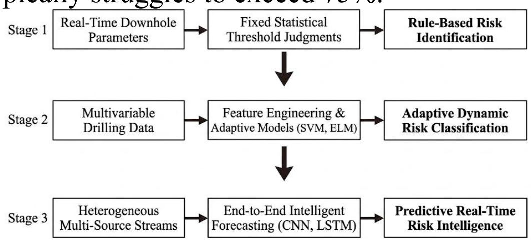

Figure 3. Schematic Diagram of the Evolution Path of the Algorithm for Dynamic Identification of Safety Risks in Deep Coal Mines During Drilling.

The core of traditional threshold algorithms lies in the construction of parameter anomaly detection models. Early studies mostly used decision boundaries based on the mean plus standard deviation multiple or mechanical energy threshold discrimination methods to conduct preliminary assessments of lithological changes and dynamic disaster risks. Although this stage laid the data foundation for subsequent intelligent development, the rigidity of fixed thresholds makes it difficult to capture nonlinear relationships and has poor robustness under deep and complex geological conditions. As mining depth increases, traditional methods gradually expose limitations such as limited interpretability and weak generalization ability, and urgently need to evolve towards more intelligent algorithms [7]. The practical experience of this stage provides important historical references and data accumulation for subsequent stages.

3.2 Machine Learning Algorithm Stage

The machine learning algorithm stage marks the transformation of dynamic identification technology during drilling to a data-driven model. This stage introduces methods such as support vector machines, extreme learning machines, fuzzy clustering, and optimized kernel extreme learning machines. By training on historical multi-source data during drilling, it achieves lithology identification, working condition diagnosis, and risk probability prediction, significantly improving the algorithm's ability to capture nonlinear features and its engineering applicability. It is particularly suitable for the complex environment of multi-parameter coupling in deep coal mines.

Compared with traditional thresholding methods, machine learning algorithms no longer rely on fixed empirical thresholds, but achieve adaptive modeling through feature engineering and parameter optimization. They can effectively handle noise, small sample size and high-dimensional characteristics of drilling data, and perform well in rock hardness perception and stuck drill condition prediction. In this stage, the algorithm realizes a closed-loop process from data acquisition to decision output through clustering analysis without prior labels or optimized extreme learning machine models. Engineering verification shows that the recognition accuracy is significantly improved compared with traditional methods. However, this stage still has problems such as relatively weak model interpretability, high dependence on large-scale data and the need to further enhance generalization ability, which provides a necessary transition for the in-depth development of deep learning integration stage. [8] The introduction of machine learning algorithms not only overcomes the rigid limitations of traditional methods, but also lays a solid technical foundation for the intelligent dynamic identification of safety risks in deep coal mines.

3.3 Deep Learning Fusion Algorithm Stage

The deep learning fusion algorithm stage represents the latest evolution of dynamic identification technology during drilling. This stage achieves end-to-end automatic feature extraction and temporal modeling through convolutional neural networks, long short-term memory networks, and multi-source data fusion architecture, significantly enhancing the identification accuracy and generalization ability under conditions of high noise and multi-field coupling in deep mines, providing efficient technical support for intelligent drilling and inherent safety in coal mines.

Deep learning fusion algorithms can automatically mine deep spatiotemporal features from multimodal data such as drilling vibration, drilling pressure, and torque, breaking through the limitations of manual feature design and showing excellent performance in coal and rock property identification and dynamic disaster risk prediction. Combining attention mechanism and edge-cloud collaborative architecture, the algorithm at this stage forms a complete intelligent system from data perception to risk classification prediction. Engineering applications show that its identification accuracy can exceed 90%. This stage also focuses on the real-time performance and robustness optimization of the model. However, it still faces challenges such as insufficient model interpretability, need to strengthen small sample adaptability, and high computational resource requirements. [9] The continuous evolution of deep learning fusion algorithms has pointed out the direction for the future development of dynamic identification technology for deep coal mines during drilling and provided key methodological support for building a transparent geology and intelligent mine system.

4. Conclusion

This study systematically reviews the evolution path of dynamic risk identification algorithms for deep coal mines during drilling. In the context of high ground stress and multi-field coupling in deep mines, the traditional threshold algorithm stage initially identified parameter anomalies by fixing statistical boundaries, laying the foundation for early risk monitoring. The machine learning algorithm stage introduced methods such as support vector machines and extreme learning machines, significantly improving the ability to capture nonlinear features and adapt. The deep learning fusion algorithm stage, leveraging convolutional neural networks, long short-term memory networks, and multi-source data fusion architecture, achieved end-to-end feature extraction and real-time risk classification prediction, resulting in a qualitative leap in identification accuracy and generalization ability. This evolution path clearly demonstrates the inherent logic of the algorithm shifting from experience-dependent to data-driven and intelligently adaptive approaches. It not only provides a complete theoretical framework for dynamic risk identification technology during drilling but also contributes methodological support for the inherent safety and intelligent mine construction of deep coal mines.

While existing algorithms have made significant progress in engineering practice, they still suffer from insufficient model interpretability, weak adaptability to small samples, and the need to strengthen robustness under extreme deep conditions. Future research can focus on refined modeling of multiphysics coupling mechanisms, real-time optimization of edge computing and federated learning, and deep integration of interpretable artificial intelligence technologies. This will further promote the evolution of drilling-while-drilling dynamic identification algorithms towards higher accuracy, stronger generalization, and greater transparency, providing continuous technical support for the safe and efficient mining of deep coal resources in my country.

References

[1] Shu, LY, Zhu, NN, Chen, J., An, S., Zhang, HJ: Theoretical method and technology of precision identification for coal and gas outburst hazard. Journal of China Coal Society 45(5), 1614–1625 (2020).

[2] Zhang, YZ, Li, QX, Li, WN, Zhong, ZC, Chen, L., Yang, DD, Chen, T.: Research and application of intelligent perception while drilling in coal mine. Coal Science and Technology 54(4), 1–13 (2026).

[3] Yue, Z., Yue, X., Yang, R., Wang, X., Li, W., Dai, S., Li, Y.: Progress of lithology identification technology while drilling. Journal of Mining Science and Technology 7(4), 389–402 (2022).

[4] Si, L., Liu, Y., Wang, Z., Gu, J., Wei, D., Dai, J., Li, X., Zhao, Y.: Coal-rock recognition during drilling of anti-punch drilling robot based on improved 1DCNN-LSTM. Journal of Mining Science and Technology 11(1), 206–217 (2026).

[5] Du, JS, Chen, J., Pu, YY, Jiang, DY, Chen, LL, Zhang, YR: Risk assessment of dynamic disasters in deep coal mines based on multi-source, multi-parameter indexes, and engineering application. Process Safety and Environmental Protection 155, 575–586

(2021).
[6] Khanal, M., Qin, J., Shen, B., Dlamini, B.: Preliminary investigation into measurement while drilling as a means to characterize the coalmine roof. Resources 9(2), 10 (2020).[7] Zhang, W., Li, C., Jin, J., Qu,
[8] Zagré, GE, Gamache, M., Labib, R., Shlenchak, V.: Machine learning algorithms for real-time coal recognition using monitor-while-drilling data. International Journal of Mining, Reclamation and Environment 38(1), 27–52 (2024).
[9] Niu, G., Zhang, K., Yu, B., Chen, Y., Wu, Y., Liu, J.: Experimental study on comprehensive real-time methods to determine geological condition of rock mass along the boreholes while drilling in underground coal mines. Shock and Vibration 2019, Article ID 1045929 (2019).
