Application of Data Mining in Well Control Management for Well Repair Operations

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Abstract. Well control in well repair operations is essential to safe and stable oilfield production, because failures in pressure control may lead to blowouts, environmental pollution, equipment damage, and even casualties. Traditional well control management mainly depends on manual inspection, experience-based judgment, and fixed emergency procedures, which makes it difficult to identify early abnormal signals in a timely and accurate manner. To improve the effectiveness of well control management, this paper discusses the application of data mining techniques in well repair operations. Time-series analysis and anomaly detection can be used to monitor the operating status of key well control equipment, while data-driven early warning models can support the identification of kick and blowout risks. By integrating equipment-state data, pressure-related signals, and operational information, data mining provides a more objective and timely basis for risk assessment and emergency response. This study shows that the introduction of data mining can strengthen process supervision, improve abnormal situation warning capability, and support the intelligent development of well control management in well repair operations.

Keywords: well control; data mining; well repair operations; anomaly detection; risk early warning

1 Introduction

Well control is a core component of well repair operations and directly affects the safety and stability of oilfield production. Because well repair is carried out under complex pressure conditions and involves multiple operational links, such as well control design, equipment configuration, process supervision, and emergency response, any failure in pressure control may lead to blowouts, equipment damage, environmental pollution, and even casualties. Therefore, effective well control management is not only a basic requirement for safe production, but also an important guarantee for maintaining operational continuity and reducing accident losses. In recent years, with the increasing complexity of drilling and well intervention environments, the need for more intelligent and timely risk identification has become more prominent [1].

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However, traditional well control management still mainly depends on manual inspection, experience-based judgment, and fixed alarm thresholds. Although these methods are useful in routine operations, they often show clear limitations when dealing with gradual degradation, multivariable coupling, and weak abnormal signals. In practice, many well control risks do not emerge as a single abrupt event, but as a continuous evolution reflected in pressure, flow, and equipment-state signals over time. This makes it difficult for conventional supervision methods to provide sufficiently early and reliable warning support, especially in dynamic operating conditions [1]. To address these challenges, recent studies have increasingly introduced data-driven monitoring and early warning methods into drilling and well control scenarios. Existing research shows that multivariate statistics, machine learning, and multi-model fusion methods can support anomaly detection, fault diagnosis, and fault prediction in drilling processes [1]. For example, Noori et al. applied deep-learning-based multivariate time-series classification to condition monitoring of the internal blowout preventer (IBOP), while Park et al. used time-series anomaly detection to identify abnormal hydraulic accumulator behavior from pressure signals. In the area of kick and overflow warning, Osarogiagbon et al. proposed an LSTM-RNN-based kick detection method using drilling time-series data, and Liu et al. further developed a data-driven overflow identification and early warning framework by combining sliding-window processing, physical feature fusion, and machine learning. In addition, Altindal et al. recently demonstrated that unsupervised methods such as PCA, Isolation Forest, and LSTM-AE can effectively detect anomalous events in multivariate drilling time-series data, highlighting the practical value of generalized anomaly detection frameworks in real-time drilling supervision [2–6]. Based on the above background, this paper discusses the application of data mining in well control management for well repair operations. The study first analyzes the importance of well control in well repair, and then focuses on how data mining can support process supervision and abnormal situation handling. Specifically, time-series analysis and anomaly detection are introduced for the condition monitoring of key well control equipment, while data-driven early warning models are used to improve the identification of kick and blowout risks. Through this discussion, the paper aims to provide a clearer technical pathway for the intelligent development of well control management in well repair operations [1][5][6].

2 The Critical Role of Well Control in Well Repair Operations

Well control during well repair operations plays a fundamental role, characterized by extensive construction areas, numerous operational points, extended durations, and significant variability. The importance of well control in these operations is primarily reflected in two key aspects.

First, in well control safety management, both single-well contingency plans and well control designs serve as the foundation of management. Particularly when managing new wells, whether scientific preliminary planning and design can be effectively implemented directly impacts production quality and safety during later stages. Based on operational analysis of process oil and gas fields, ensuring the standardization and scientific rigor of well control construction design schemes is crucial during field development. This approach not only helps achieve corporate production objectives and protect personal and property safety, but also enhances overall engineering standards while ensuring smooth execution of well control operations (As illustrated in Figure 1, blowout accidents may lead to extremely serious fire hazards and catastrophic safety consequences). Therefore, the design of well control contingency plans plays a vital role in determining the quality of actual well maintenance work, serving as the key factor in achieving economic efficiency targets and ensuring safety and quality outcomes throughout the project lifecycle.

Second, comprehensive well control preparation serves as the safety prerequisite for conducting well repair operations. At construction sites, various aspects such as equipment layout and electrical wiring require attention. To ensure perimeter security, staff must implement scientific arrangement management based on specific conditions and prepare all materials during construction to meet project requirements. Additionally, when emergencies occur, proper spatial arrangements enable rapid evacuation of personnel and equipment. Therefore, enterprises and workers should conduct advance safety inspections at construction sites, ensuring precise verification of well control measures while evaluating their rationality. Before formal construction begins, regulatory authorities should coordinate to enhance personnel safety awareness and well control skills. This helps workers accurately recognize potential risks, strengthen responsibility consciousness, thereby significantly reducing accident probabilities while improving emergency response capabilities.

Fig. 1. The flame from the gas blowout accident in Kaixian, Chongqing reached a height of 100 meters.

3 Optimization Measures for Well Control inWell Repair Operations

3.1 Preparatory Work Before commencing

Well repair operations, management personnel are required to organize relevant staff to design technical measures for the well control plan and simultaneously brief on emergency response plans. Prior to formal commencement, comprehensive inspections must be conducted. This includes self-inspections of injection equipment, well control devices, and blowout prevention tools at the construction site. Identified issues should be rectified and reported to the management department upon meeting standards. The management department will then conduct acceptance inspections to ensure that operations such as cementing fluid application and installation of well control equipment comply with design specifications. Figure 2 shows technicians inspecting the well control device before operation.

Fig. 2. Technicians inspect the well control device.

Secondly, each production team should develop emergency response plans and conduct regular drills. This includes promptly performing overflow detection, initiating alarm procedures, and executing proper well shutdown protocols. Additionally, companies must establish comprehensive position accountability systems with assigned personnel for round-the-clock monitoring. Professional teams should then conduct project acceptance inspections to verify the actual implementation of well control measures at construction sites.

3.2 Implement Process Supervision

During well repair operations, process supervision should be extended from manual inspection to data-driven condition monitoring of key well control equipment. In practical applications, pressure, valve-state, and actuation signals can be treated as time-series data, allowing abnormal fluctuations and early degradation features to be detected before functional failure occurs. This is important because many faults in well control systems develop gradually and are difficult to identify through conventional threshold-based inspection alone. Existing studies have shown that data mining methods are applicable to critical well control components, especially for pressure-related monitoring and multivariate sequence analysis. Table 1 summarizes representative well control equipment and the corresponding data mining methods.

Table 1. Representative well control equipment and corresponding data mining methods

Well control equipment / monitoring object	Typical data	Data mining technique	Reference
Internal blowout preventer (IBOP)	Multivariate operational sequences and activity states	Multivariate time-series classification with deep learning	[2]
Hydraulic accumulator	Pulsating pressure signals	Time-series anomaly detection	[3]
Standpipe pressure-related kick monitoring	Pressure trend and coupled drilling signals	LSTM-based temporal pattern recognition	[4]

For example, Noori et al. developed a condition monitoring framework for the internal blowout preventer by combining discrete event systems with deep-learning-based multivariate time-series classification [2]. Park et al. applied anomaly detection methods to hydraulic accumulator pressure data and demonstrated that abnormal pulsating pressure can be effectively identified from sensor signals [3]. These studies suggest that process supervision in well repair should focus on continuous monitoring of critical equipment states rather than relying only on periodic checks.

3.3 Prompt Handling of Abnormal Situations

When abnormal situations occur during well repair operations, emergency handling should not rely only on manual judgment and fixed alarm thresholds. A more effective strategy is to introduce data mining techniques to establish a blowout-risk early warning model, so that the evolution of risk can be identified before a serious loss-of-control event occurs.

To provide a more concrete implementation, the early-warning model is formulated as a multivariate time-series learning framework. The input consists of multi-source monitoring signals, including standpipe pressure, wellhead pressure, and equipment-state variables. At time step t, the multivariate monitoring signal can be represented as:

$$x_t = \left[p_t^{sp}, p_t^{wh}, e_t^{(1)}, e_t^{(2)}, \ldots, e_t^{(m)}\right]$$

where p_t^{sp} and p_t^{wh} denote the standpipe pressure and wellhead pressure at time step t, respectively, and $e_t^{(k)}$ denotes the k-th equipment-state variable. A sliding window strategy is adopted to transform raw sequential data into fixed-length samples, enabling the model to capture temporal dependencies in well control conditions.

Let x_t denote the multivariate monitoring signal at time step t, and a sliding window with length L is used to construct the input sequence as $X_i = [x_i, x_{i+1}, \ldots, x_{i+L-1}]$. The temporal model then extracts sequence features and outputs the corresponding risk probability, which can be expressed as $\hat{y}_i = \sigma(Wh_i + b)$, where h_i denotes the learned temporal representation, W and b are trainable parameters, and $\sigma(\cdot)$ is the sigmoid activation function.

The model can be trained using historical monitoring data with labeled normal and abnormal states. Binary cross-entropy is adopted as the loss function, and parameters are optimized using stochastic gradient descent or Adam optimizer. The loss function can be written as:

$$\mathcal{L} = -\frac{1}{N}\sum_{i=1}^{N}[y_i \log(\hat{y}_i) + (1-y_i)\log(1-\hat{y}_i)]$$

where N is the number of training samples, $y_i$is the ground-truth label, and $\hat{y}_i$is the predicted risk probability of the i-th sample. Key hyperparameters include the sliding window length, learning rate, batch size, and hidden dimension, which can be selected according to the monitoring frequency and data scale in practical applications.

Existing studies provide practical technical support for this idea. Osarogiagbon et al. proposed an LSTM-RNN-based kick detection method using d-exponent and standpipe pressure time-series data, and showed that temporal learning [4]. Zhu et al. further developed a temporal autoencoder framework for gas kick warning. In their BiLSTM-AE model, normal sequential patterns are first learned from historical time-series data, and then reconstruction error is used to identify abnormal risk sequences [7]. In addition, Liu et al. combined sliding-window processing, physical feature fusion, and a random forest model to identify overflow risk in managed pressure drilling, and reported overflow recognition accuracy above 99%, indicating that data mining can provide reliable support for abnormal warning in drilling and well control scenarios [5]. Figure 3 illustrates a data-mining-based framework for blowout risk early warning. The figure clearly illustrates the data flow from multi-source input signals to temporal feature extraction and final risk prediction, providing a visual interpretation of the proposed framework.

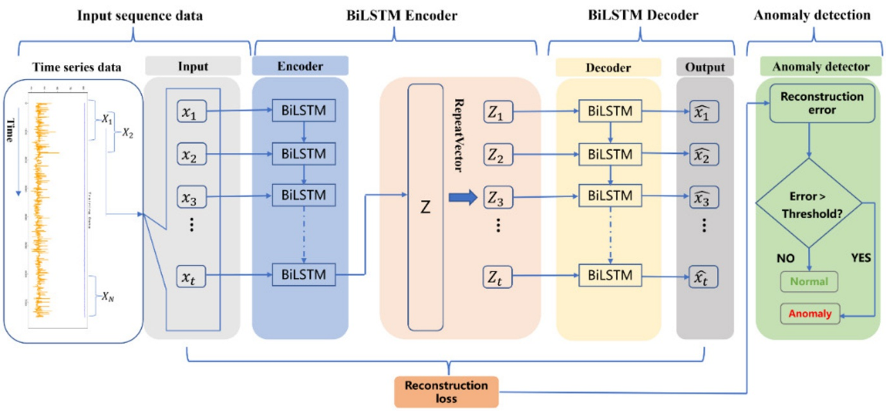

Fig. 3. Framework of a data-mining-based blowout risk early warning model ((adapted from the structure of the BiLSTM-AE model in Zhu et al. [7]))

Based on the above studies, the prompt handling process in well repair operations can be upgraded as follows. First, real-time data such as standpipe pressure, wellhead pressure, and key equipment-state signals are collected continuously. Second, temporal features are extracted through sliding-window analysis or sequence learning. Third, the trained warning model outputs a dynamic risk score or abnormality signal. Finally, once the warning result exceeds the predefined threshold, on-site personnel should immediately initiate conventional well control measures, including shutdown, isolation of ignition sources, and wellhead protection. In this way, data mining does not replace traditional emergency response procedures, but strengthens their timeliness, objectivity, and scientific basis. [5][7]

4 Conclusion

This paper reviewed the importance of well control in well repair operations and further discussed the application of data mining techniques in well control management. The main finding is that conventional well control practices, although essential, are often limited by manual inspection, experience-based judgment, and fixed alarm thresholds, whereas data-driven methods can provide more timely and objective support for equipment condition monitoring and abnormal risk warning. By introducing time-series analysis, anomaly detection, and early warning models into process supervision and abnormal situation handling, this study highlights a feasible pathway for improving the intelligence and effectiveness of well control management in well repair operations. This paper is positioned as an application-oriented technical discussion rather than a case study or a systematic review. Its main purpose is to clarify the potential role of data mining in well control management for well repair operations and to summarize a feasible technical pathway for condition monitoring and risk early warning under this context. The value of this paper lies in linking traditional well control management with emerging data mining techniques and showing their practical potential in equipment monitoring, risk identification, and emergency decision support. However, this study is mainly a discussion based on published research and typical application scenarios, and it does not include field-level validation with large-scale real-time data from specific well repair projects. Future research should focus on integrating multi-source monitoring data, optimizing predictive model accuracy, and promoting the deployment of real-time data-driven early warning systems to support safer and smarter well control management in oilfield operations.

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