Research on the Quantitative Evaluation and Methods of Drilling Overflow Risk Based on While-Drilling Information

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Abstract

In order to solve the problems of insufficient generalisation ability and poor interpretability of evaluation results in the complex geological environment of the current data-driven overflow risk assessment model, this paper proposes a quantitative overflow risk assessment method based on the combination of CNN-LSTM data-driven model and fuzzy reasoning system. The data features were extracted, the overflow risk was predicted, the fuzzy comprehensive evaluation method was further adopted, the membership function was generated based on the normal distribution fitting historical data, the risk probability threshold was dynamically calibrated, the risk was refined into low, medium and high levels, and the expert experience was integrated through fuzzy reasoning rules to improve the transparency and flexibility of overflow risk assessment. The experimental results show that the accuracy of the proposed method is 99.95%, and the false alarm rate is only 0.5%, which significantly improves the adaptability and reliability of risk assessment compared with the traditional static threshold method, and enhances the interpretability of the model through feature visualisation and dynamic rules, which provides intelligent decision support with both high precision and strong robustness for drilling safety.

Keywords

Overflow Risk; Composite Model; CNN-LSTM; Quantitative Evaluation.

1. Introduction

In recent years, with the continuous increase in drilling depth, the geological conditions have become more complex, and the difficulty of drilling has gradually increased[1]. There are a large number of uncertainties and randomness issues during the drilling process, which also increases well control risks. As a precursor to blowouts, the timely identification and assessment of influx are of significant importance in reducing the probability of blowout occurrence and ensuring safe drilling[2]. The occurrence of influx is usually accompanied by changes in directly indicative parameters such as increased outlet flow and total pit volume, as well as abnormal fluctuations in indirectly indicative parameters such as increased hook load and decreased riser pressure. Therefore, accurately analyzing these data changes is key to identifying and assessing the risk of influx.

Traditional methods that rely on human intervention to solve problems encountered in engineering have obvious limitations, whereas machine learning can, to some extent, solve problems that human effort cannot. With the rapid development of machine learning and deep learning technologies, data-driven methods for influx risk identification and assessment have gradually become a research focus[3-4]. In recent years, researchers have increasingly utilized specific drilling information as key indicators of influx risk, employing various intelligent algorithms (such as Monte Carlo simulation, LSTM, and CNN) to build intelligent risk assessment models for influx, providing important support for risk management under complex conditions [5-8]. However, as black-box models, data-driven models rely on the quality of features and labels[9-10]. Their accuracy may be affected by data variations, thus reducing the acceptance of assessment results[11]. Fuzzy reasoning systems are more transparent and easier to understand in decision-making processes[12]. They quantify uncertainty and fuzziness, simulate human thinking, and convert expert knowledge into rules[13]. Due to the complexity and variability of drilling engineering, expert knowledge is crucial in identification and assessment[14], and fuzzy reasoning systems can effectively combine data with expert experience to achieve accurate evaluation and early warning of drilling risks.

Therefore, this paper proposes a quantitative assessment method for influx risk that combines data-driven models with fuzzy reasoning, aiming to effectively integrate the advantages of both knowledge-driven and data-driven approaches. First, a CNN-LSTM model is utilized to calculate the probability of influx risk. CNN is used to mine the deep-level features of input parameters, transforming complex real-time monitoring data into more representative latent representations. LSTM uses these feature representations to compute the influx risk probability values. Secondly, a fuzzy comprehensive evaluation method is applied to determine the critical risk probability threshold, further refining the risk levels. Through assessment and analysis, it is found that this method performs excellently in terms of accuracy and timeliness of risk assessment, providing more reliable technical support and decision-making basis.

2. Construction of a Drilling Blowout Risk Model

2.1. Data Processing

2.1.1. Parameter Selection

The data used in this article are all real-time data collected on-site. In order to reduce model redundancy and improve diagnostic effectiveness, it is necessary to optimally select input features. Through data analysis, it can be observed that there are significant changes when overflow occurs, while other parameters do not show a regular sequential change trend. Combined with the expert knowledge summarized in the oilfield, these four parameters are selected as the discriminant parameters for overflow risk. Therefore, this article selects hook load, mud tank volume, riser pressure, and inlet-outlet flow difference as key features for drilling overflow risk modeling.

2.1.2. Data Normalization

Due to the different dimensions of various parameters and the significant numerical differences caused by the differences in dimensions, this can lead to excessively long prediction times or large errors in the final results during the model prediction process due to the presence of singular samples. Therefore, it is necessary to normalize the training data. This article uses the max-min normalization method to process the data dimensionlessly.

$$x_{new} = \frac{\left(x - x_{\min}\right)}{x_{\max} - x_{\min}} \tag{1}$$

In the formula: x_{new} represents the normalized value of the data, x represents the original value of the data, x_{max} represents the maximum value of all sample data for the selected feature, and x_{min} represents the minimum value of all sample data for the selected feature.

2.2. Model Building

2.2.1. Model Structure

This model uses a one-dimensional convolutional neural network (1D CNN) for data convolution processing. The proposed deep learning framework based on 1D CNN-LSTM has its parameters detailed in Table 1. The 1D CNN-LSTM model consists of 1 input layer, 3 CNN layers, 3 MaxPooling layers, 2 dropout layers, 2 LSTM layers, 1 fully connected layer, and 1 output layer.

Table 1. Parameter settings for CNN-LSTM

Name	Type	Input shape	Output shape
Input Layer	Feature input	200,1,1	200,1,1
CNN Layer 1	Conv1d/Relu/MaxPool1d	200,1,1	100,1,128
CNN Layer 2	Conv1d/Relu/MaxPool1d	100,1,128	49,1,64
CNN Layer 3	Conv1d/Relu/MaxPool1d	49,1,64	23,1,32
LSTM Layer1	Lstm 1d/ Relu/dropout	736,1,1	64,1,1
LSTM Layer2	Lstm 1d/ Relu/dropout	64,1,1	64,1,1
Identification/prediction	Fully connected layer	64,1,1	2,1,1/50,1,1
Output Layer	Feature output	2,1,1/50,1,1	2,1,1/50,1,1

2.2.2. Comparison of Model Results

This article compares the accuracy rate, false negative rate, and false positive rate of the Random Forest algorithm, CNN algorithm, LSTM algorithm, and CNN-LSTM algorithm for overflow prediction, with the results from the test set shown in Figure 1. Random Forest is a non-sequential model, while the others are sequential models. It is concluded that the accuracy rate of sequential models is higher than that of non-sequential models and their false positive rate is lower than that of non-sequential models, indicating that sequential models are better at predicting overflow risk than non-sequential models. Although the false negative rate of CNN, as a sequential model, is higher than that of the non-sequential model Random Forest, the overall trend shows that the false negative rate of sequential models is superior to that of non-sequential models. Among the single sequential models, the LSTM model performs better than the CNN model, achieving an accuracy rate of 90.7%, a false negative rate of 8.6%, and a false positive rate of 8.9%. Comparatively, the CNN-LSTM has the highest accuracy rate among the four at 92.8%, with a false positive rate of 3.9% and a false negative rate of 6.8%, which are also better than the other three models.

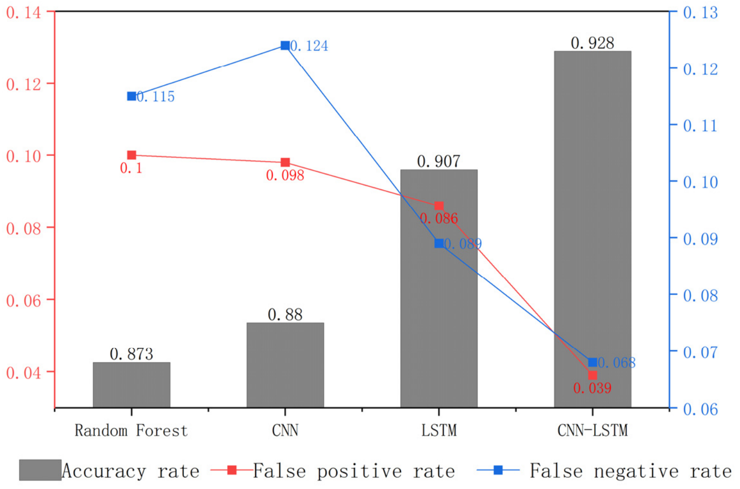

Fig 1. Comparison results of different models

3. Quantitative Evaluation of Overflow Risk

3.1. Overflow Risk Classification

In view of the practical situation where there are many influencing factors and it is difficult to make accurate and confident judgments about the importance of all factors, this paper applies the Analytic Hierarchy Process to determine the weights of various factors in decision-making through decomposition, judgment, and synthesis. This serves to reasonably determine the direction vector. The final determined factor set includes:$\mathrm{U} = \{\mathrm{U}_1, \mathrm{U}_2, \mathrm{U}_3, \mathrm{U}_4\}$. U_1 = major hook load, U_2 = vertical pipe pressure, U_3 = mud tank volume, U_4 = inlet and outlet flow difference. Under a certain evaluation criterion, the overflow risk levels are classified, referred to as the risk level set, $\mathrm{V} = \left(\mathrm{v}_1, \mathrm{v}_2, \ldots, \mathrm{v}_\mathrm{g}\right)$. Based on this, considering the characteristics of difficulty in horizontal well drilling, the value is determined to be g = 3, for the risk level set $\mathrm{V} = \{\mathrm{L}ow\ risk, \mathrm{M}edium\ risk, \mathrm{H}igh\ risk\}$.

This article uses the entropy weight method to determine the weight results of four parameters: the large hook load is 0.2446, the riser pressure is 0.7174, the mud tank volume is 0.0237, and the inlet and outlet flow difference is 0.0143. A membership function is introduced to determine the membership degree of single-factor risk levels. Based on the actual situation of drilling engineering, three risk levels are proposed, and then the membership degree functions of each level are provided using the methods of fuzzy sets in fuzzy mathematics.

(1) High risk, its membership function is:

$$A(x)=\begin{Bmatrix} 1, x<0.024 \\ \dfrac{0.048-x}{0.024}, 0.024\le x\le 0.034 \\ 0, x>0.034 \end{Bmatrix} \tag{2}$$

(2) Medium risk, its membership function is:

$$A(x)=\begin{Bmatrix} \dfrac{x-0.024}{0.01}, 0.024\le x<0.034 \\ 1, 0.034\le x<0.048 \\ \dfrac{0.072-x}{0.024}, 0.048\le x<0.072 \\ 0, x>0.072 \end{Bmatrix} \tag{3}$$

(3) Low risk, its membership function is:

$$A(x)=\begin{Bmatrix} 0, x<0.048 \\ \dfrac{x-c}{d-c}, 0.048\le x\le 0.072 \\ 1, x>0.072 \end{Bmatrix} \tag{4}$$

4. Model Evaluation

In order to evaluate the predictive accuracy of the CNN-LSTM overflow risk determination model, four performance indicators are selected: Confusion Matrix, Accuracy, True Positive Rate (TPR), and False Positive Rate (FPR). The definition of the confusion matrix is shown in Table 3-8. There are two cases of correct classification by the model: one is that the model predicts 'negative' or 'no' (N), and the actual result is also 'negative' (N), denoted as TN; the other is that the model predicts 'positive' or 'yes' (P), and the actual result is also 'positive' (P), denoted as TP. Similarly, there are two cases of incorrect classification by the model: one is that the model predicts 'negative' or 'no' (N), and the actual result is 'positive' (P), denoted as FN;

the other is that the model predicts 'positive' or 'yes' (P), and the actual result is 'negative' (N), denoted as FP. Thus, the formulas for calculating Accuracy, True Positive Rate (TPR), and False Positive Rate (FPR) are given as follows.

$$Accuracy = \frac{TP + TN}{TN + TP + FN + FP} \tag{5}$$

$$FPR = \frac{FP}{FP + TN} \tag{6}$$

$$TPR = \frac{TP}{TP + FN} \tag{7}$$

Figure 2 shows the confusion matrix of the overflow risk prediction results. Based on the analysis of the model's prediction results, the model's accuracy value is calculated to be 0.928, with a false positive rate of 0.068 and a miss rate of 0.039. This indicates that the combined method of the composite model and fuzzy reasoning for overflow risk classification assessment provides additional support for overflow prediction, overcoming the limitations of static binary calibration and fixed threshold classification.

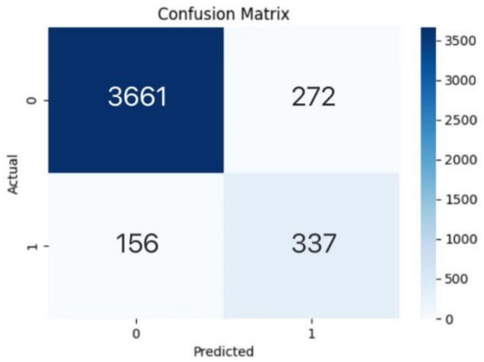

Fig 2. Confusion matrix

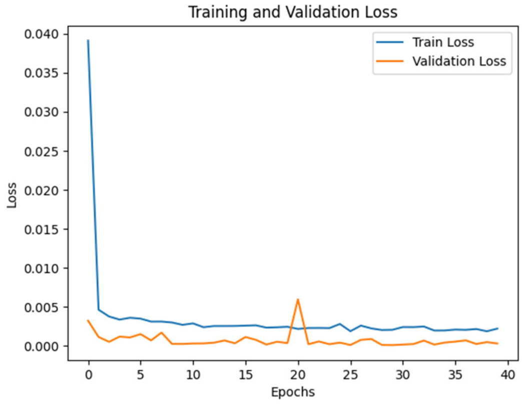

Fig 3. Loss function

The loss function graph of the model training is shown in Figure 7. The training loss trend quickly drops from nearly 0.035 to about 0.005, indicating that the model is quickly learning data features in the early stages. The subsequent loss stabilizes below 0.005 with no significant fluctuations, suggesting that the model has largely converged. The validation loss trend decreases from 0.01 to 0.005, but the rate of decline is slower than that of the training loss, possibly due to a difference in distribution between the validation set and the training set. A noticeable peak occurs at round 20 (about 0.015), reflecting a brief overfitting of the model to the validation set during this phase. Finally, the loss stabilizes between 0.005 and 0.01, without further decline, indicating that the model's generalization capability has reached a bottleneck.

This suggests that the learning rate has not diminished with the training progress, leading to unstable parameter updates and a self-correction of the model after overfitting on specific features.

In summary, the overflow risk prediction model established based on CNN-LSTM can effectively predict the occurrence of blowout incidents during drilling, verifying the feasibility of the quantitative assessment method for overflow risk that combines data-driven models and fuzzy reasoning.

5. Conclusion

1) The classification of overflow risk can effectively capture spatial and sequential features in the data collected during drilling monitoring, and the introduction of fuzzy reasoning enhances the method's adaptability and flexibility in dealing with fuzzy boundaries.

2) Compared to the fixed threshold calibration methods, the established overflow risk prediction method has a very high accuracy, further verifying the stability and reliability of this method in overflow risk identification.

References

[1] Qian Zhang. Research and Implementation of Drilling Accident Recognition System Based on Machine Learning[D]. Xi'an Shiyou University, 2021.

[2] Wanjun Hu, Wenhe Xia, Yongjie Li, et al. Intelligent identification method for safety risks during gas drilling operations[J]. Oil exploration and development, 2022, 49(02): 377-384.

[3] Gensheng Li, Xianzhi Song, Zhaopeng Zhu, et al. Research progress and prospects of intelligent drilling technology[J]. Oil drilling technology, 2023, (04).

[4] Tingting He, Qiang Zhang. The current status and development trends of knowledge graphs in oil and gas exploration and development[J]. Natural gas industry, 2024, 44(09): 55-67.

[5] Zixu Guo, Biao Ma, Shuai Zhang, et al. Research progress and technological prospects of deep learning in oil and gas production forecasting [J]. Natural gas industry, 2024, 44(09): 88-98.

[6] Chunlan Zhao, Yao Qu, Bing Wang, et al. A new method for predicting the severity of drilling accidents based on 2D-CNN deep learning [J]. Natural gas industry, 2022, 42(12): 95-105.

[7] Yanan Sheng, Zhichuan Guan, Ming Luo, et al. Quantitative evaluation method for drilling engineering risk based on uncertainty analysis [J]. Journal of China University of Petroleum (Natural Science Edition), 2019, 43(02): 91-96.

[8] Yuqiang XU, Kuan LIU, Baolun HE, et al. Risk pre-assessment method for regional drilling engineering based on deep learning and multi-source data[J]. Petroleum Science, 2023, 20(6):3654-3672.

[9] Wenhe XIA, Zongxu ZHAO, Chengxiao LI, et al. Intelligent risk identification of gas drilling based on nonlinear classification network[J]. Petroleum Science, 2023, 20(5):3074-3084.

[10] Yuhao WANG, Jiasheng HAO, Fan ZHANG, et al. Adaptive LSTM early warning method for kick detection in drilling[J].Control Theory&Applications, 2022, 39(3):441-448.

[11] MIN Chao, Guoquan WEN, Xiaogang LI, et al. Research progress and application prospect of interpretable machine learning in artificial intelligence of oil and gas industry[J].Natural Gas Industry, 2024, 44(9):114-126.

[12] ARTUN E, KULGA B. Selection of candidate wells for refracturing in tight gas sand reservoirs using fuzzy inference[J].Petroleum Exploration and Development, 2020, 47(2):413-420.

[13] Qiuju XIE, Yanbao GUO, Min ZHANG, et al. Risk assessment of girth welds of high-grade steel pipelines based on fuzzy theory and index method[J]. Oil&Gas Storage and Transportation,2022, 41 (11):1291-1297.

[14] Zhaopeng ZHU,Lin ZHU, Xianzhi SONG, et al. A generalization method of intelligent ROP prediction under mechanism constraints[J]. Natural Gas Industry, 2024, 44(9):179-189.