COMBINING DRILLING CONDITION ANALYSIS WITH UNSUPERVISED TIME SERIES MODELS FOR KICK MONITORING

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ABSTRACT

With the continuous development of petroleum exploration and production technology and the increasing complexity of geological conditions, the problem of narrow-margin safe drilling has become a major challenge in the field of petroleum exploration and development. Kick is also one of the high-frequency, high-hazard accidents in drilling. To reduce drilling costs and improve drilling safety, it is crucial to accurately monitor kicks and prevent their further development. A method for monitoring kick, based on the variation of logging parameters, currently exists. However, it does not take into account the impact of abnormal conditions such as pump stoppages on the outlet flow rate and the total volume of drilling fluid in the tank, which can lead to false alarms. In order to improve the accuracy of risk identification and reduce the false alarm rate, a kick monitoring method is proposed that combines drilling conditions with an unsupervised Bidirectional Long Short-Term Memory Autoencoder (BiLSTM-AE). This model simultaneously considers past and future information through forward and backward propagation, effectively extracting temporal features from sequences using bidirectional information. The proposed method was tested using kick monitoring data from 3 wells. The experimental results indicate that the recognition accuracy of the kick intelligent monitoring model based on BiLSTM-AE is 88.85%, surpassing other existing intelligent monitoring models. When combined with abnormal conditions such as pump stoppages, the model's false alarm rate is reduced by 9.33%.

This research can provide a theoretical foundation and important technical reference for accurate kick risk monitoring, especially in conditions where kick risk data labels are lacking. Moreover, it holds significant potential for practical field applications.

Keywords: Kick Monitoring, Drilling Condition, BiLSTM-AE

NOMENCLATURE

LSTM  Long Short-Term Memory
RNN  Recurrent Neural Network
BiLSTM  Bidirectional Long Short-Term Memory
AE  Autoencoder
DDTW  Derivative Dynamic Time Warping
TP  True Positive
TN  True Negative
FP  False Positive
FN  False Negative
FPR  False Positive Rate

1. INTRODUCTION

The research on drilling kick risk monitoring methods is in a continuous phase of development and evolution. Researchers are actively exploring new technologies and approaches on the basis of traditional methods to enhance the timeliness, accuracy, and adaptability of monitoring. Traditional methods mainly focus on monitoring a small number of key parameters, leading to the drawbacks of a single parameter, the need for threshold
setting, and poor timeliness and accuracy. To address these challenges, advanced technologies such as artificial intelligence and machine learning are gradually being introduced, forming diverse and comprehensive kick monitoring methods. False alarms are a common issue in kick risk monitoring, impacting normal drilling operations, prolonging drilling cycles, increasing drilling costs, and limiting the on-site application of kick monitoring methods[1].

Orban et al.[2] proposed the small error flowmeter that has become a key tool for early mud flow monitoring. By reducing errors, this method provides more accurate and reliable mud flow measurements in practical drilling operations, thereby offering reliable data support for the timely detection of potential kick events. Stokka et al.[3], on the other hand, utilized sensors to record acoustic phase differences to detect gas intrusion, focusing on monitoring drilling fluid parameters from different physical perspectives. Methods such as the drilling fluid pool liquid level monitoring[4] and the in/outflow rate difference method are commonly used kick monitoring techniques on drilling sites. Although these methods are simple, effective, and easy to apply, their risk identification accuracy is lower and false alarm rates are higher due to insufficient consideration of the correlations and constraints between drilling conditions and monitoring parameters, as well as the difficulty in accurately setting thresholds[5]. In practical operations, the underground environment is influenced by numerous factors, making it challenging for traditional methods to model the complex relationships between these factors. Therefore, when underground conditions change, traditional monitoring systems may not adapt promptly and accurately, limiting their applicability in complex drilling conditions.

In recent years, artificial intelligence methods have been widely applied in the field of kick monitoring, achieving a series of significant advancements. Zhang He et al.[6] integrated various parameters to design a kick early warning system based on a fuzzy expert system, which can rapidly and accurately issue kick warnings. Ekaterina Gurina et al.[7], on the other hand, constructed a classification model based on a decision tree gradient boosting. Utilizing Measurement While Drilling(MWD) data, the model exhibits relative insensitivity to sample size and data quality, can handle missing data, and quickly learns a large number of features. The leave-one-out cross-validation criterion is used as a quality measure for rapid learning.

Liang et al.[8-11] proposed an intelligent early warning method based on the correlation between kick risks and casing pressure changes. Firstly, they used the slope of data point values as a clustering criterion, considering the actual slope values during the intersection of pressure gradients and slope change durations. They applied a Density-Based Spatial Clustering of Applications with Noise (DBSCAN) with adjusted threshold settings, considering the time series to enhance risk identification accuracy. Secondly, they established a kick monitoring model using a genetic algorithm and BP neural network (GA_BP). By optimizing model parameters and reducing errors caused by single feature parameter selection, the performance of the model was significantly improved, with a 73.73% reduction in error compared to the BP neural network model and higher accuracy. Thirdly, they introduced a new early kick warning model established through pattern recognition and K-means dynamic clustering, overcoming lag and accuracy issues of traditional monitoring methods. Finally, they proposed an improved information entropy method, enhancing the traditional fuzzy C-means (FCM) clustering algorithm, and developed an intelligent kick early warning model based on the improved algorithm. Experimental results indicate that the model outperforms existing models in predicting kick incidents, demonstrating higher stability and reliability. Through practical applications, these methods and models not only accurately predict drilling kick incidents, providing a reliable basis for rapid monitoring, but also hold potential value for industrial promotion. In 2022, Elmgerbi A et al.[12] proposed a method for automatically analyzing real-time drilling data. This method accurately detects and verifies the existence of the most common downhole drilling risks at their onset, allowing corrective measures to be taken to reduce the negative impact and associated costs of detected downhole malfunctions. Yin et al.[13, 14], on the other hand, analyzed time-series data from on-site drilling processes to early detect gas invasion. They processed the raw on-site data through data collection, data cleaning, feature scaling, anomaly detection, data labeling, and dataset splitting. After comparing the effects of three algorithms, namely Long Short-Term Memory neural network (LSTM), Recurrent Neural Network, and Sparse Autoencoder Support Vector Machine, the research team found that the LSTM algorithm performed the best, achieving an accuracy of 87%. This result indicates that, for early detection tasks related to gas invasion, the LSTM algorithm exhibits significant advantages in terms of effectiveness.

In order to enhance the accuracy of kick risk identification and reduce false alarm rates, this study conducted a thorough analysis of the effects of pump-on and pump-off conditions on kick risk recognition. Building upon this analysis, an unsupervised time-series model, Bidirectional Long Short-Term Memory Autoencoder (BiLSTM-AE), was introduced and applied to the field of kick monitoring. This research innovatively proposes an intelligent kick monitoring method that combines drilling conditions with the BiLSTM-AE network.

2. METHODOLOGY
2.1 Long Short-Term Memory

The Long Short-Term Memory (LSTM) neural network is an improved type of Recurrent Neural Network (RNN). It was initially proposed in 1997 by Hochreiter and Schmidhuber, and further enhanced in 1999 by Alex Graves et al.[15], who introduced the concept of a forget gate. The LSTM structure is illustrated in Figure 1. This modification led to the development of a more systematic and comprehensive LSTM framework, effectively addressing the gradient vanishing and exploding issues commonly found in traditional RNNs. Since then, LSTM has been widely applied in various sequence information prediction scenarios. Compared to the unit model structure of internal repetitive networks in RNNs, LSTM protects and
controls the model’s memory of sequence information by incorporating three gate control units, one tanh layer, and one cell state (Ct) for state transmission. The cell state, spans the entire LSTM and changes slowly over time, transmitted from the previous state Ct-1. On the other hand, the hidden state, ht, undergoes corresponding calculations at different nodes and often changes more rapidly. The formula for the forget gate is represented as Equation (1).

\[ f_t = \sigma(W_f[h_{t-1}, x_t] + b_f) \]  

(1)

Where \( h_{t-1} \) is the output from the previous stage, \( x_t \) is the input for the current stage, and \( \sigma \) is the sigmoid activation function.

The input gate determines the information to be added based on the current input and the hidden state of the memory unit from the previous time step. It decides how much of the important information to retain in vector \( \tilde{C}_t \). \( i_t \) is obtained from the sigmoid function, \( \tilde{C}_t \) is obtained from the tanh function, and the state is updated according to Equation (4).

\[ i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \]  

(2)

\[ \tilde{C}_t = \tanh(W_c[h_{t-1}, x_t] + b_c) \]  

(3)

\[ c_t = f_t c_{t-1} + i_t \tilde{C}_t \]  

(4)

Here, \( W_i \) and \( b_i \) are the weight and bias vectors of the sigmoid layer, while \( W_c \) and \( b_c \) are the weight and bias vectors of the tanh layer.

The sigmoid activation function in the output gate is used to determine the features of the output cell state:

\[ o_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \]  

(5)

\[ h_t = o_t \cdot \tanh(c_t) \]  

(6)

Where \( W_o \) and \( b_o \) are the parameters of the output gate.

2.2 Bidirectional Long Short-Term Memory

The LSTM model can only predict the next time step based on historical information, thus learning the risk representation parameters and features of historical moments but unable to learn features of future moments. This unidirectional transmission limitation does not take into account the forward and backward evolution of temporal sequences. In contrast, the Bidirectional Long Short-Term Memory network (BiLSTM) has two separate state transmission belts for information transfer, transmitting information both backward and forward[16]. The bidirectional layer is essentially composed of two opposite-direction LSTM layers: a forward LSTM and a backward LSTM. By modeling both past and future time-series data, it can better leverage the temporal characteristics of the sequence, improving the model’s predictive accuracy. This approach allows for a comprehensive exploration of the connections in risk time-series data.

The BiLSTM network structure, as shown in Figure 2, consists of two independently operating LSTM layers. One LSTM layer processes the input sequence in chronological order, while the other LSTM layer processes the input sequence in reverse order. The outputs of these two LSTM layers are then concatenated.

\[ \tilde{h}_t = LSTM(x_t, \tilde{h}_{t-1}) \]  

(7)

\[ \tilde{h}_t = LSTM(x_t, \tilde{h}_{t-1}) \]  

(8)

Where, \( \tilde{h}_t \) is t moment forward LSTM network hidden layer state; \( \tilde{h}_t \) is t moments reverse LSTM network hidden layer state; LSTM is the LSTM unit; \( x_t \) is t moment input; \( \tilde{h}_{t-1} \) is t-1 moment state forward LSTM network hidden layer state; \( h_{t-1} \) is t-1 moment state back LSTM network hidden layer state.

2.3 Autoencoder

An autoencoder is an unsupervised learning neural network model used to learn an effective representation of data. It consists of an encoder and a decoder, which together map input data to a latent space and then reconstruct the original data from the latent representation[17]. The fundamental goal is to learn a compact representation of the data by compressing and decompressing, capturing the essential features within the data. An autoencoder is composed of an encoder and a decoder. The structure of the autoencoder is shown in Figure 3.
Given pump stroke rate and outlet flow rate data sequences denoted as $X = \{x_1, x_2, \ldots, x_n\}$ and $Y = \{y_1, y_2, \ldots, y_n\}$ respectively, First, take the derivative of each of the two sequences, i.e.,

$$x'_i = x_2 - x_1, i = 1$$

$$x'_i = (x_i - x_{i-1}) + (x_{i+1} - x_{i-1})/2, 2 \leq i < m$$

$$x'_m = x_m - x_{m-1}, i = m$$

(11)

Where $x_i$ represents the i-th element in $X$, and $X'$ is the sequence after differentiation. The calculation method for $Y'$ is similar.

Next, standardize the sequences $X'$ and $Y''$, i.e.,

$$X'' = \left\{ x'_i - \mu_x \right\}/\sigma_x$$

(12)

Where, $\mu_x$ and $\sigma_x$ are the mean and standard deviation of sequence $X'$, $X''$ is the sequence after standardization, and $x''$ represents the i-th element in $X''$.

In the drilling construction process, the kick risk is typically monitored by observing changes in the drilling fluid outlet flow rate and the volume of the drilling fluid pool. However, if the impact of pump-on and pump-off operations on the outlet flow rate and drilling fluid pool volume is not considered, it can lead to the issue of false alarms. To eliminate the risk of false alarms caused by pump-on and pump-off conditions, accurate identification of these conditions is needed before conducting kick and well leakage monitoring. Given that pump-on and pump-off operations directly result in pump stroke rate and noticeable changes in the outlet flow rate, this study proposes a method for discriminating pump-on and pump-off conditions based on Derivative Dynamic Time Warping (DDTW)[18]. By analyzing the relative change trends of pump stroke rate and outlet flow rates, this method can effectively identify pump-on and pump-off conditions, thereby improving the accuracy and reliability of the monitoring system. The approach obtains relevant shape information by estimating the first-order derivative of the sequence, effectively addressing singularity issues, reducing computational complexity, and enhancing the method's generalization capabilities.
max(m, n) \leq A \leq m + n - 1 \quad (13)

Constraint 3: Path Curve Continuity Constraint - The curve of the path can only move one grid along the horizontal axis, vertical axis, or diagonal axis, and cannot skip grids.

Constraint 4: Path Curve Monotonicity Constraint - The curve is only allowed to move to the right, down, or diagonally down-right.

There are many paths L that satisfy the constraint conditions, and a path can be represented as \( L = \{l_1, l_2, \ldots, l_p, \ldots, l_A\} \). The calculation of elements in the path is as follows:

\[
d(l_p) = (x''_i - y''_k)^2 \quad (14)
\]

Where \( l_p \) represents the coordinates of the p-th point in path L.

Forming the set of all possibilities for path L, denoted as M, there exists an optimal path in M such that \( \sum_{p=1}^{A} d(l_p) \) is minimized. The Dynamic Time Warping distance for sequences X and Y is then:

\[
d_{\text{DTW}}(X,Y) = \min_{M} \sum_{p=1}^{A} d(l_p) \quad (15)
\]

3. Kick Monitoring Model

3.1 Dataset

Utilizing logging data from 10 wells in the Tarim Oilfield, China, an kick risk dataset was constructed. The data from 7 wells were used as training and validation data for the model, while the data from the remaining 3 wells were used for model testing. The identification performance of the intelligent model relies on the quality of the training data. To avoid the impact of missing values, outliers, and other factors on the model's recognition accuracy, data preprocessing is required before training the model.

Due to factors such as on-site measurement errors, equipment malfunctions, or other anomalies, drilling data may contain missing values and outliers. Linear interpolation and boxplot methods are two common and effective approaches. Linear interpolation leverages the linear relationship between data points, allowing estimation of missing values based on existing observed values, thus filling gaps in the dataset while preserving the overall data trend. Boxplot analysis helps identify outliers, i.e., values deviating from the normal distribution. Additionally, by using a 60-point sliding average filtering method, we can eliminate high-frequency noise in the data, highlight the overall trend, and further enhance data effectiveness and stability. To eliminate the dimensionality differences between different features, enhance model stability, and improve training performance, normalization is applied to preprocess the data. Normalization ensures that variations between different measurement indicators do not significantly impact analysis and modeling.

Based on on-site expert experience, this study selected the following parameters as inputs for the model: outlet flow rate, total pool volume, standpipe pressure, total hydrocarbons, and pump stroke rate. The data representation for these parameters is shown in Table 1.

<table>
<thead>
<tr>
<th>outlet flow rate(%)</th>
<th>total pool volume(\text{m}^3)</th>
<th>standpipe pressure(Mpa)</th>
<th>total hydrocarbons(%)</th>
<th>pump stroke rate(sp m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean ( \text{Me} )</td>
<td>25.3</td>
<td>85.4</td>
<td>3.5</td>
<td>10.3</td>
</tr>
<tr>
<td>Min ( \text{Min} )</td>
<td>0</td>
<td>96.1</td>
<td>0</td>
<td>1.5</td>
</tr>
<tr>
<td>Max ( \text{Max} )</td>
<td>50.2</td>
<td>109.8</td>
<td>7.7</td>
<td>80.6</td>
</tr>
</tbody>
</table>

3.2 Data Sample Construction

As the logging data collected at the drilling site exhibits a certain temporal and spatial correlation, meaning that the data at the current moment may have a certain impact on the future results, the kick monitoring problem can be treated as a problem of multivariate time series. Time series models depend on the order of the data; in other words, changing the order of the same data will result in different model outcomes. Therefore, before training the model, it is necessary to sort the original dataset based on the collection time and construct samples for multivariate, multi-step sequences.

3.3 Model Construction

The structure of BiLSTM-AE is shown in Figure 5, where both the encoder and decoder are BiLSTM. To train the BiLSTM-AE model, the stochastic gradient descent optimization algorithm is employed, and the mean squared error is used to measure the reconstruction error between the encoder and decoder. During training, the state transmission issue of the BiLSTM layer is also considered, and early stopping is applied to prevent overfitting. Finally, the trained BiLSTM-AE model is applied to the analysis and prediction of drilling data. By comparing the differences between reconstructed data and original data, further analysis of the characteristics and patterns of drilling data is conducted.
Firstly, set the reconstruction error threshold and kick recognition sensitivity S for the time series autoencoder model. Next, input the test time series data into the model to obtain the reconstruction error of the data. Then, use the least squares method to calculate the slope for each time series data. Finally, compare the slope T of the time series with the kick risk sensitivity S. When T ≥ S, it is determined that a kick incident has occurred, and when T < S, it is determined that no kick incident has occurred.

### 3.4 Evaluation metrics

The Confusion Matrix is a commonly used model evaluation tool that illustrates the model’s predictions for each category, as shown in Table 2. The Confusion Matrix includes four metrics: True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN), which can be used to calculate other evaluation metrics. To compare the recognition performance of different models, accuracy and false positive rate (FPR) are used as the model evaluation metrics.

<table>
<thead>
<tr>
<th>True result</th>
<th>Forecast result</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Positive class</td>
</tr>
<tr>
<td>Positive class</td>
<td>TP</td>
</tr>
<tr>
<td>Negative class</td>
<td>FP</td>
</tr>
</tbody>
</table>

The accuracy formula is given by Equation (16).

\[
\text{Accuracy} = \frac{TP + TN}{TP + FN + TN + FP} \tag{16}
\]

The false positive rate (FPR) formula is given by Equation (17).

\[
\text{FPR} = \frac{FN}{TP + FN} \tag{17}
\]

### 4. RESULTS AND DISCUSSION

To validate the performance of the unsupervised BiLSTM-AE model and the combined model with drilling conditions constraints, we first compare the monitoring results of the LSTM, BiLSTM, LSTM-AE, and BiLSTM-AE models using the processed drilling monitoring data. The effects before and after incorporating the pump on and off conditions are also compared. Accuracy and false positive rate are used as evaluation metrics to assess the model performance.

#### 4.1 Without considering drilling conditions

To verify the advantages of the BiLSTM-AE model in kick monitoring, the following models were constructed using the parameters of outlet flow, total drilling fluid pool volume, standpipe pressure, total hydrocarbon, and pump shock: LSTM model, BiLSTM model, LSTM-AE model, and BiLSTM-AE model. The models were trained using the same dataset and model hyperparameters, and then tested using a test set. The recognition accuracy and false alarm rate of the four models were compared and analyzed.

When testing the LSTM-AE model and BiLSTM-AE model, it is necessary to set the threshold for the reconstruction error. If the data reconstruction error exceeds the predetermined threshold, the unsupervised autoencoder model classifies the data as an anomaly. The threshold in this study is set to 0.02 and can be adjusted based on data characteristics and field requirements. This threshold is determined based on an understanding of the mechanism knowledge and data features. Additionally, using the least squares method to fit the time series autoencoder anomaly sequence, we observe whether it conforms to the trend of kick risk. To further confirm kick risk, we fix the time series slope at 0.0018 based on domain knowledge. Similarly, this threshold can be adjusted as needed.

We compared and analyzed the performance of the LSTM, BiLSTM, LSTM-AE, and BiLSTM-AE models to identify the advantages of different models in capturing features. The experimental comparative results are shown in Figure 6. The recognition accuracy of the four models was 84.32%, 86.93%, 86.29%, and 88.85%, respectively, and the false alarm rates were 19.45%, 18.79%, 18.03%, and 17.65%, respectively. It can be observed that unsupervised models improved by nearly 2 percentage points compared to supervised models. The LSTM-AE model improved by 1.97% compared to the LSTM model, and the BiLSTM-AE model improved by 1.92% compared to the BiLSTM model. Among the four models, the BiLSTM-AE model showed the best performance, indicating that the BiLSTM-AE model can more comprehensively capture time series relationships and has better classification performance.
4.2 Considering drilling conditions.

To test the impact of drilling conditions on kick monitoring models, the DDTW method was used to determine pump on and off conditions. The results of this determination were then combined with the output results of the intelligent models. The parameter changes during pump on and off conditions are shown in Figure 7. If fluctuations in logging parameters were caused by pump on and off conditions, the model's output results were transformed to indicate no kick risk, thereby reducing the false alarm rate. Experimental results showed that after incorporating pump on and off conditions, the false alarm rates of the four models were reduced to 15.46%, 13.67%, 11.54%, and 8.32%, respectively. The BiLSTM-AE model exhibited the most significant reduction in false alarm rate, decreasing by 9.33%.

(1) Compared to existing kick risk monitoring models, the BiLSTM-AE model better captures the temporal features of parameters. It can effectively utilize historical and future information in the time series of drilling parameters. The accuracy of the BiLSTM-AE model is nearly 2 percentage points higher than that of the supervised BiLSTM model.

(2) Based on DDTW and analyzing the relative change trends of pump strokes and outlet flow rates, this method can effectively identify the on and off pump conditions. The discernment results constrain the outcomes of the unsupervised intelligent model, effectively reducing false alarms by 9.33%.

The unsupervised learning approach proposed in this study overcomes the challenge of limited field risk data samples, making it applicable in a broader range of field scenarios. In the future, we aim to explore the interpretability of the model and establish a risk monitoring model with better robustness.

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