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Early warning of deep-water drilling influx based on machine learning

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ABSTRACT

During deep-water drilling, the pressure window between pore pressure and leakage pressure is narrow, leading to frequent gas kick incidents. Loss of control can lead to severe gas kick or well blowout, resulting in incalculable losses. Therefore, the early detection of gas kick to allow for efficient well control strategies has been a focus of research in recent years. This paper presents a machine learning-based approach and research framework for early warning of gas kick during deep-water drilling. This approach is also applicable to handle other complex downhole incidents.

KEY WORDS: Deep-water drilling; narrow pressure window; gas kick; early warning; machine learning

INTRODUCTION

Safety is the lifeline of deep-water drilling, and blowout is the greatest threat to safety. Gas kick is a precursor to blowout and may lead to disasters like blowout explosion in the Gulf of Mexico (Pranesh et al., 2017). This paper aims to develop early warning systems for gas kick risks in deep-water drilling operations, which is a valuable research endeavor in preventing potential accidents. It serves as an essential barrier to safeguard deep-water drilling operations. It has significant implications for enhancing emergency management and on-site emergency response in deep-water drilling.

Drilling is an essential aspect of deepwater oil and gas exploration and development. However, the narrow pressure window available during deep-water drilling increases the risk of gas kick and blowout incidents. As natural gas circulates from the well to the surface through the drilling fluid, the pressure in the wellbore drops, and the volume of natural gas expands, causing the amount of drilling fluid discharged to increase as it approaches the surface. If gas kick is not discovered and controlled promptly, it can lead to serious safety and environmental risks, resulting in significant economic losses and even blowout. The Deepwater Horizon blowout was a shocking reminder of the importance of early detection and control of gas kick in the narrow pressure window of deep-water drilling. Currently, two significant challenges are faced:

Challenge 1: Traditional deep-water drilling gas kick monitoring is prone to lag and inaccuracies, resulting in poor quality data sample sets. For example, in the case of *LW22-1-1*, the deepest ultra-deepwater well in the Pacific with a water depth of 2616.30m, the use of 21-inch (outside diameter) risers results in a volume of 530.28m^3. This leads to prolonged cycle delays of up to 90 minutes, causing significant monitoring lag. Furthermore, strong wind (25.70m/s), waves (4.50m), and currents (1.03m/s) lead to fluctuations in semi-submersible platform elevation. These fluctuations also cause sedimentation in the outlet pipeline/mud pit. As a result, the monitoring data is inaccurate, and the sample set quality is poor. The lag in monitoring and lack of early warning leads to frequent deepwater gas kick incidents, resulting in wellbore failure.

Researchers have studied different monitoring methods for downhole, riser, and wellhead and have identified the following (Liao et al., 2020; Sharma et al., 2023; Wang et al., 2020; Zhang et al., 2023).

(1) The drilling parameters and downhole pressure measurements in the downhole can indirectly reflect the downhole conditions when encountering complex strata.

(2) The Doppler ultrasonic sensor in the riser (without drill rod conditions) can timely detect the gas kick after the bubbles invade the riser, which helps improve the monitoring efficiency.

(3) Installing a mass flow meter at the wellhead can achieve high-precision mass flow measurement, which helps improve monitoring accuracy.

If the three different monitoring methods for the downhole, riser, and wellhead are integrated, it can fundamentally eliminate the lag and inaccuracy of traditional wellhead mud pit monitoring and ultimately solve the problem of early monitoring of deep-water drilling gas kick.

Challenge 2: The highly nonlinear mapping between monitoring parameters causes early warning inaccuracy based on mechanism-based models. Complex gas-liquid-solid three-phase flow transfers accompany the deep-water drilling gas kick process. When gas from the stratum invades the wellbore, the wellbore contains stratum gas, drilling fluid liquid, and rock debris solid, ultimately leading to extremely complex, highly nonlinear mapping relationships between the deepwater gas kick and various monitoring parameters. The conventional mechanism-based models, programmed routinely, cannot accurately predict the early stage of deep-water drilling gas kick, while machine learning methods can fit the nonlinear mapping relationship between different monitoring parameters from high dimensions, effectively completing specific pattern recognition tasks. Research shows that some scholars have used machine learning methods such as genetic wavelet neural networks and Bayesian networks to conduct deep-water drilling gas kick risk recognition studies (Nhat et al., 2020; Xie et al., 2018). However, these models do not fully consider the long-term sequence characteristics of deep-water drilling gas kick. In the preliminary stage, the authors built a real-time classification model to determine the risk level of deep-water drilling gas kick (Yin et al., 2021) and a real-time regression model for the rate of deep-water drilling gas kick based on Long Short-Term Memory (LSTM) network (Yin et al., 2022). These models analyzed “real-time alarming" of deep-water drilling gas kick. However, the main problem of the model is that it only focuses on "real-time alarming" and does not implement "early warning", which is not sufficient to scientifically and reasonably formulate well control strategies.

This paper focuses on the application of machine learning on early warning of gas kick in deep-water drilling. When a deep-water drilling gas kick occurs, changes in monitoring parameters such as downhole, riser, and wellhead occur, resulting in abnormal fluctuations. Machine learning can be used for early warning of deep-water drilling gas kick by training a model to fit the mapping rules of abnormal fluctuations in monitoring parameters when gas kick occurs. Compared with traditional recognition methods, machine learning-based early warning of deep-water drilling gas kick has good efficiency and accuracy. This paper proposes a comprehensive early monitoring method of "Downhole-Riser-Wellhead" multi-source data fusion for early warning of deep-water drilling gas kick. This method involves collecting high-quality sample set data and applying machine learning to the entire process. A machine learning model is established and applied in field practice, winning a valuable time window for well control strategy making and reducing well control challenges and potential well blowout risks during deep-water drilling. This paper has vital theoretical significance and engineering application value.

In this paper, a simulation experiment for deep-water drilling gas kick is presented and a gas kick data sample for early warning model building is established. TensorFlow and Python 3.6 version Keras deep learning model package with neural network algorithms were used to create a deep-water drilling gas kick early warning machine learning model. The model was constantly optimized in test verification, and the knowledge distillation method was finally used to simplify the deep-water drilling gas kick early warning machine learning model. Compared with ExxonMobil's Drilling Advisory System, Noble Drilling, and NOV's Smart Kick detection systems, the model in this paper employed advanced deep learning algorithms and could be deployed on devices with lower computing capabilities.

DATA COLLECTION AND PROCESSING

The performance of machine learning models is highly dependent on the quality and size of the sample dataset. The importance of data is far greater than the importance of the model. Only when enough data is available can the model be optimized, and high-performance machine learning models be obtained (Alzubi et al., 2018). However, the limited availability of deep-water drilling gas kick accident cases due to data confidentiality and security considerations presents a challenge for scholars in developing intelligent recognition machine learning models for these cases. To address this challenge, full-scale deep-water drilling gas kick flow simulation experiments were conducted based on rich field experience and case studies from the South China Sea to achieve comprehensive monitoring from the wellhead to the downhole. These experiments effectively simulated the actual deep-water drilling process. It provided a large number of high-quality sample datasets, which were analyzed and pre-processed to provide data foundation for establishing machine learning models.

Data collection

This section will introduce the data collection method and device when deep-water drilling gas kick occurs, as well as the process of establishing the data sample set. A short new side-bypass pipe in riser was designed and developed, and an ultrasonic Doppler sensor was installed in the side-bypass pipe to monitor the migration law of gas kick. A comprehensive "Downhole-Riser-Wellhead" monitoring method was adopted. To carry out a series of simulation experiments, the original sample data from gas kicks was collected. The response characteristics of gas kick was studied and the evolution mechanism of the whole process of the bubble-gas kick-well blowout was identified.

Reasonable sensor layout

The conventional method of installing Doppler sensors on the exterior of the riser in Fig. 1 is simple and convenient. However, it is interfered by the drill stem, and the rotation of the drill stem can make it difficult for the sensor to launch and receive signals. In Fig. 2, a short new side-bypass pipe in riser was designed and developed in this paper to ensure fluid consistency. The design allows drilling fluid with bubbles to flow through the main riser and the side-bypass pipe, while ultrasonic Doppler sensors installed outside the side-bypass pipe were used to monitor gas kick data. The side-bypass pipe forms an independent fluid flow channel, effectively solving the problem of signal distortion caused by the rotation of the drill rod in conventional Doppler monitoring installed outside the riser.

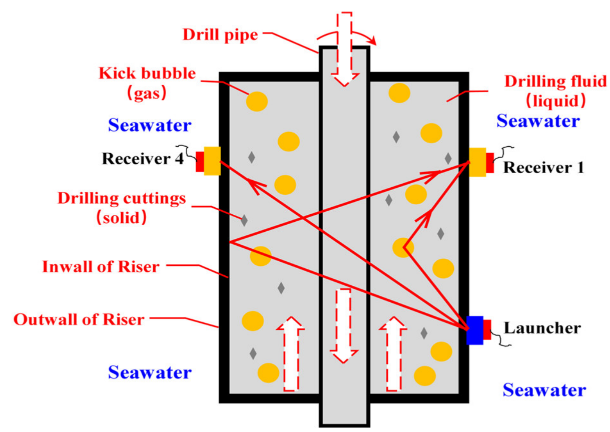

Fig. 1 Conventional layout of Doppler sensor outside the riser (Yin et al., 2020)

This paper focused on the unique aspect of early detection of gas kick in deep-water drilling by installing multiple Doppler sensors on the short new side-bypass pipe in riser. In Fig. 2, the arrangement consists of one transmitter and six receivers placed at the same height with a 60-degree spacing. Based on the data collection frequency and the velocity of the drilling fluid, the receivers are placed correctly at the downstream of the transmitter to receive the offset acoustic signals that follow the movement of the drilling fluid.

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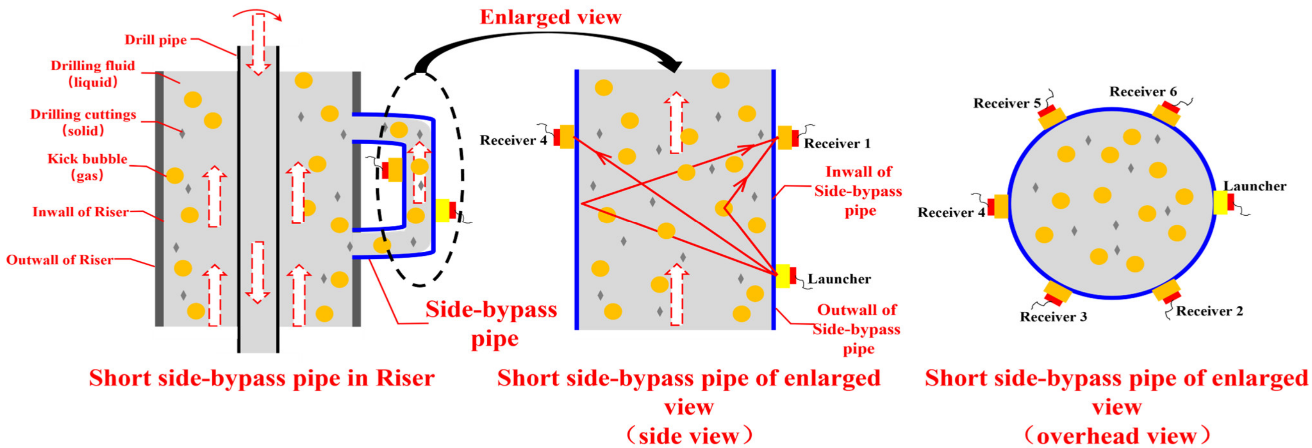

Fig. 2 Short new side-bypass pipe in riser and Doppler sensor layout scheme

Comprehensive monitoring mode

Based on the existing simulation experiment setup, a comprehensive monitoring method adopted for the "Downhole-Riser-Wellhead" is shown in Fig. 3. A series of downhole gas kick simulations were conducted by injecting compressed air using the industrial air compressor. The response characteristics of gas kick were studied, and the time-sensitivity and changes in monitoring parameters that consider the delayed time effect of long-cycle drilling were found during the gas kick process. Monitoring data was collected to study the process of gas escaping from the downhole to the riser to the wellhead through the drilling fluid. The mechanism of the whole process evolution from gas bubble to gas kick to well blowout was studied during the continuous decrease of wellbore pressure and volume expansion.

Simulating gas kick by injecting compressed air into the bottom of a well, the changes in the pressure gauge, riser Doppler sensor, wellhead mass flow meter, and comprehensive logging unit were closely monitored. The data for the bottom well pressure, continuous Doppler acoustic data of riser, the wellhead mass flow meter, comprehensive well logging data, and bottom well injection rate were recorded and stored. These data allowed us to study each monitoring parameter's effectiveness and corresponding changes and analyze gas kick's response characteristics and evolution mechanisms. By changing the wellbore injection conditions, the gas kick was simulated with different rates, thus building a data sample set for early warning machine learning models for deep-water drilling gas kick.

Data processing

Pre-processing of raw data is a critical stage in machine learning (Obaid et al., 2019). In this paper, research on data cleaning, signal-to-noise ratio analysis, feature normalization, and outlier removal to pre-process the raw data was carried out. These tasks eliminated errors caused by sensors and human operation fluctuations, improved data accuracy, and reduced false alarm rates. The time-domain characteristics of Doppler acoustic waves was studied, effective features were extracted, and correlation analysis of the monitoring parameters was conducted to determine the input feature parameters. The research process is shown in Fig. 4.

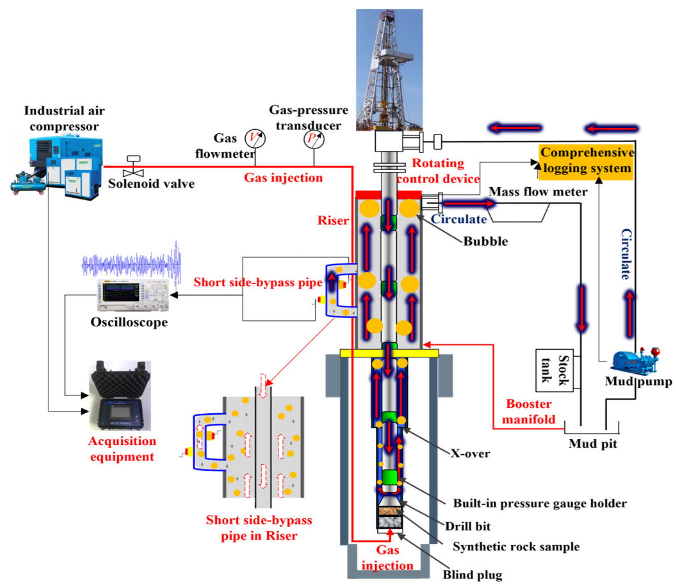

Fig. 3 Simulation scheme of gas kick in deep-water drilling

The response of ultrasonic Doppler signal to gas kick through the short side-bypass pipe in riser is complex. This complexity is due to factors such as the rate of gas kick, drilling fluid discharge, drilling fluid density, and fluid performance. As a result, extracting effective features from the signals is challenging. The use of feature extraction methods based on time-frequency transformation and linear transformation is essential for extracting the effective features of the ultrasonic multi-pulse signal and is a crucial scientific consideration in the study of early warning for deep-water drilling gas kick.

This paper examines the relationship between the time domain characteristics of Doppler ultrasonic waves and factors such as the rate of injection of air, the volume of drilling fluid, the density of drilling fluid, and the performance of drilling fluid. The data is processed through methods such as the Fourier transform and wavelet transform to reduce noise. Both time-frequency transformations (such as fast Fourier transform and short-time Fourier transform) and linear transformations (such as principal component analysis, independent component analysis, and linear discriminant analysis) were used to extract effective features

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such as the peak amplitude, wave speed, dominant frequency, and decay coefficient of the Doppler ultrasonic signals (Gençer et al., 2013). The correlation between monitoring parameters was analyzed using the Seaborn library in Python and the Heatmap function. The relationship between wellhead monitoring parameters (mud pit volume parameters, mass flow meter parameters, etc.), riser monitoring parameters (Doppler ultrasonic signals: amplitude, velocity, dominant frequency, decay coefficient, etc.), and downhole monitoring parameters (drilling parameters: drilling speed, drilling pressure, weight on bit, standpipe pressure, torque, downhole wireline measurement parameters, etc.) was studied to determine the input feature parameters.

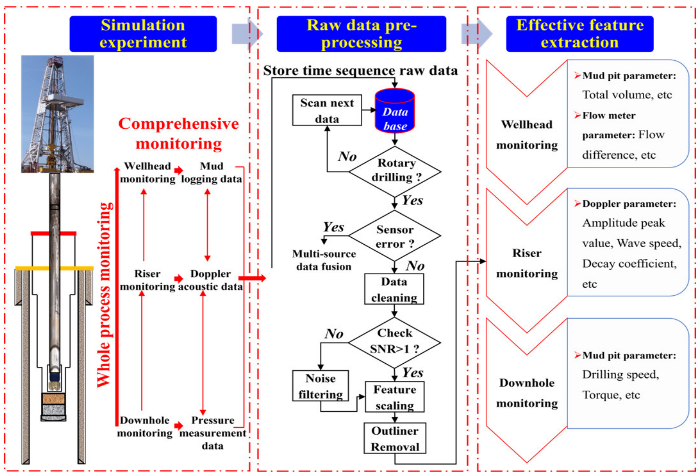

Fig. 4 Data collection method of gas kick sample in deep-water drilling (Yin et al., 2022)

DEVELOPMENT OF EARLY WARNING MACHINE LEARNING MODEL

The long-term sequence and multi-level, multi-layer, multi-source data fusion of deep-water drilling gas kick were considered. A neural network algorithm was chosen to establish the foundation for the model. Based on the differential time lag of deep-water drilling, different early warning time windows were selected to study their sensitivity. The sample set was divided into a training set, a validation set, and a test set. The hyperparameters and structural design were optimized using optimization algorithms on the training set. Early stopping strategies were used on the validation set to improve the model's training efficiency and generalization ability. Based on the initially complex model that had been well-trained, knowledge distillation methods were used to guide the training of a simplified model. Finally, an early warning machine learning model was developed. The research process is shown in Fig. 4.

The long-term delay time of deep-water drilling was found to impact deep-water drilling gas kick. The deep-water drilling gas kick was determined by the data from the current time and the time interval before and after it, resulting in the long-term sequence feature of early warning for deep-water drilling gas kick. The data from different monitoring locations (downhole, riser, and wellhead) and different dimensions (10^{-2} to 10^{3}) in deep-water drilling gas kick requires the machine learning model to have the ability to integrate multi-level, multi-layer, and multi-source data. The dual features of long-term sequence and multi-level, multi-layer, and multi-source data integration made establishing the early warning machine learning model for deep-water drilling gas kick challenging. To save model training time and improve prediction accuracy, Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Bayesian (Bayes) optimization algorithms, etc., were used for model hyperparameter tuning and structural optimization design. The established early warning machine learning model had strong generalization and robustness capabilities. Therefore, developing the early warning machine learning model for multi-source data integration and deploying the model on edge devices with limited memory and computing resources under real-world constraints is another crucial scientific issue in the study of early warning for deep-water drilling gas kick.

Firstly, this paper analyzes the characteristics of deep-water drilling gas kick with the double features of long-term sequence and multi-level, multi-layer, multi-source data fusion. Three gates (forget gate, input gate, and output gate) are introduced in the Long Short-Term Memory-Recurrent Neural Network (LSTM-RNN) model to control the flow of features and loss characteristics, and the "short-term memory" and "long-term memory" are analyzed (Hochreiter et al., 1997). The bidirectional LSTM (Bi-LSTM) model's bidirectional RNN characteristics are discussed. The forward RNN model uses past information, while the backward RNN model uses future information (Huang et al., 2015). The model structure of the Bi-LSTM model is shown in Fig. 5.

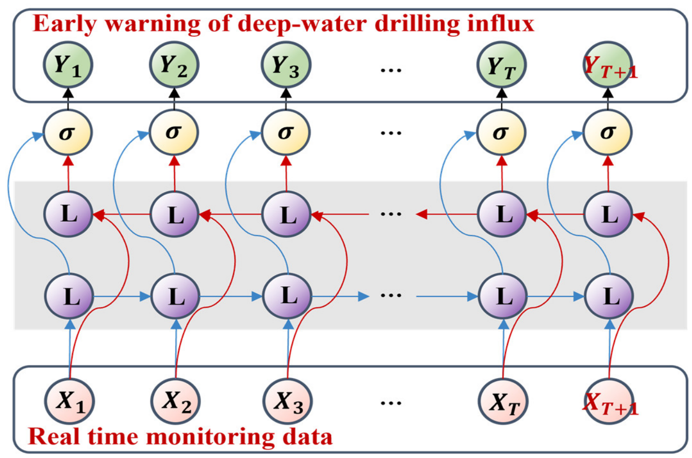

Fig. 5 The Bi-LSTM model structure

The Gated Recurrent Unit (GRU) model introduces two gate characteristics ("reset gate" captures short-term dependencies in the sequential data, and "update gate" captures medium-term dependencies in the sequential data) (Cho et al., 2014). Compared to the LSTM-RNN model, the Sequence to Sequence (Seq2Seq) model introduces the encoder-decoder structure to extract features from variable-length sequential data and uses gradient clipping and gradient reduction methods to effectively control gradient explosion and gradient disappearance during the training process (Sutskever et al., 2014). The model structure of the Seq2Seq model is shown in Fig. 6. Compared to the Seq2Seq model, the Transformer model introduces the multi-head attention mechanism and positional encoding. It focuses on multiple dependencies and spatial position in information in the sequential data. Additionally, multiple adaptive pooling layers and multi-level self-regression networks are introduced to capture and extract short-term dependencies in the sequential data (Vaswani et al., 2017). The model structure of the Transformer model is shown in Fig. 7. The Informer model updates the attention implementation mechanism compared to the Transformer model, effectively reducing the algorithm's time complexity (Yin et al., 2021). The Temporal Convolutional Network (TCN) model is based on the convolutional neural network structure and introduces residual connections, dilated convolutions, and causal convolutions to achieve flexible transformation of the receptive field,

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reducing the probability of gradient disappearance or gradient explosion to a certain extent (Bai et al., 2018). The model structure of the TCN model is shown in Fig. 8.

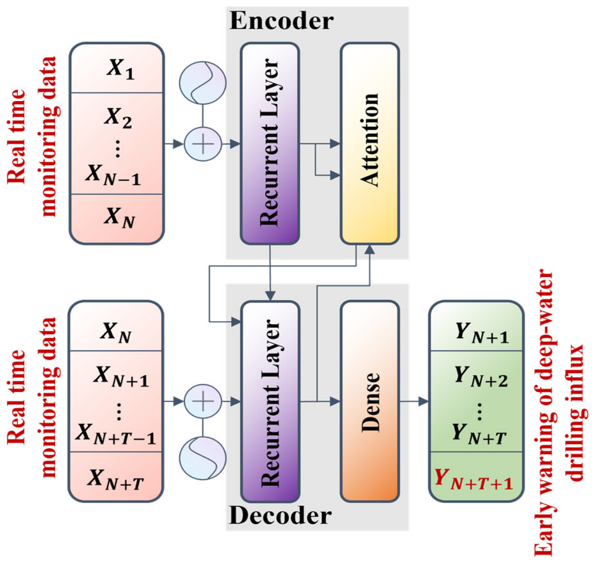

Fig. 6 The Seq2Seq model structure

The algorithm structure analysis and principal comparison were conducted to select the algorithm suitable for learning time-series information and dealing with the problem of deep-water drilling gas kick problem.

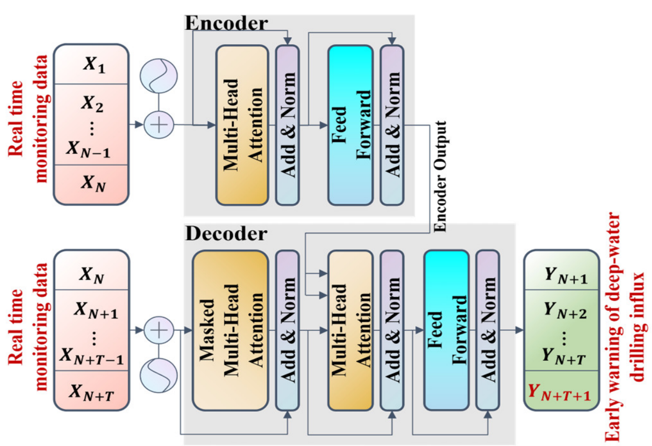

Fig. 7 The Transformer model structure

Subsequently, based on the heterogeneity of the deep-sea drilling cycle arrival time delay, five different early warning time windows were selected for building machine learning models and studying the sensitivity of the time window. The sample set was divided into a training set, validation set, and testing set for model development, model validation, and model testing, respectively.

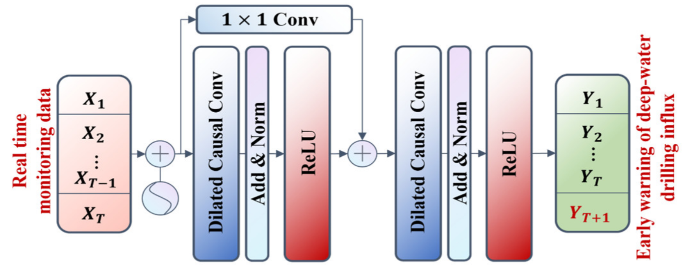

Fig. 8 The TCN model structure

Finally, the model development process utilized K-fold cross-validation to study the model fitting method. On the training set, various optimization algorithms such as Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and Bayesian optimization were used. It was done to optimize the regularization method, optimization algorithm, and hyperparameters, such as mini-batch size, as well as the number of hidden layers and nodes in the model structure. Due to limitations in training time and computational resources, the early stopping strategy was adopted on the validation set. The loss function value on the validation set during the training process was used as a monitoring metric. When the number of iterations (in which the monitoring metric no longer decreased) exceeded the maximum early stopping step, the training was stopped, and the best model performance was achieved.

Due to the conflict between the required timeliness of the early warning system for deep-water drilling gas kick and the actual low efficiency of computation on the edge devices, a knowledge distillation method was used to retrain the simplified model (Hinton et al., 2015). The best model from the initial training was selected as the teacher model, and a model with a smaller parameter scale was selected as the student model. By constructing a loss function that measures the difference between the teacher and student model predictions, the teacher model was able to guide the training of the student model. Finally, a machine learning distillation model was obtained that can be deployed on the edge devices at the site.

EARLY WARNING MACHINE LEARNING MODEL TEST

During the model testing process, the generalization ability and robustness of the established distillation model were tested on the test set using appropriate comprehensive performance measurement evaluation metrics. The machine learning model with the best performance was packaged as a pickle file.

The pickle-saved model was deployed, and a deep-water drilling gas leak early warning system was developed. The well control strategy was established and applied to representative working cases in testing. The research process is shown in Fig. 9.

Based on the above process, a machine learning distillation model was deployed. The input feature parameters data of the "Downhole-Riser-Wellhead" early comprehensive monitoring was used to achieve early prediction of gas kick rate in Fig. 10. The early warning of deep-water drilling gas kick risk was achieved using different time windows. It allowed a valuable time window for well control strategy formulation, reduced the well control challenges and potential well blowout risk during deep-water drilling, and effectively protected the safety of deep-water drilling operations.

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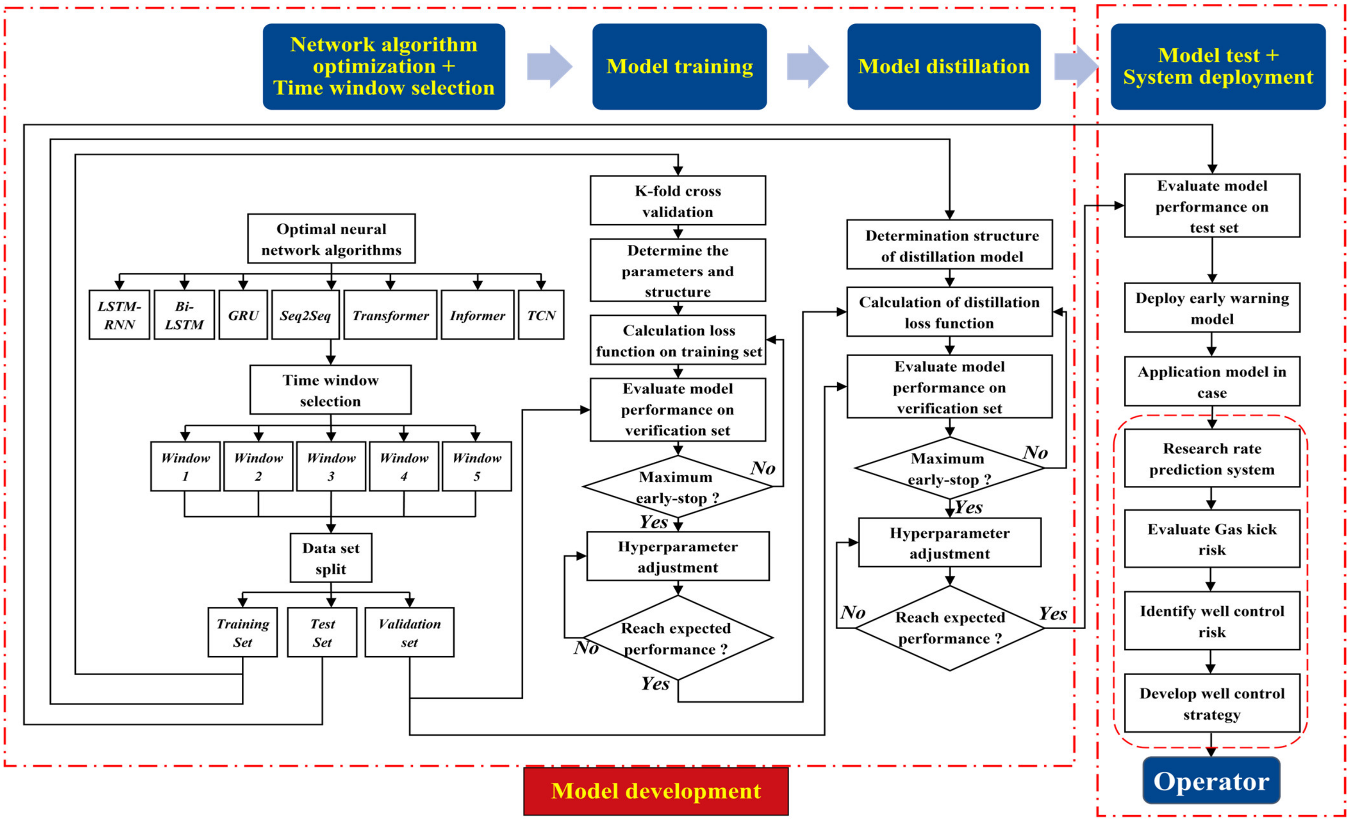

Fig. 9 Scheme of machine learning model development and model test for early warning of gas kick in deep-water drilling (Yin et al., 2022)

DEPLOYMENT OF EARLY WARNING SYSTEM FOR GAS KICK IN DEEP-WATER DRILLING

Based on the data processing and model establishment approach described above, a system for early warning of gas kick in deep-water drilling has been implemented. This system aims to reduce the challenges of well control and potential well blowout risks and effectively guarantee safe operations in deep-water drilling.

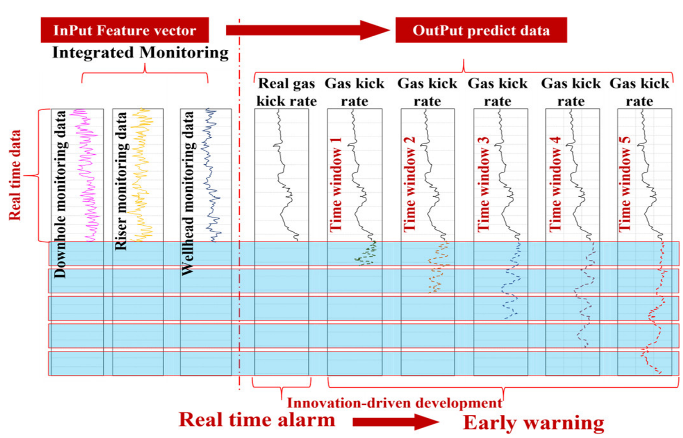

Fig. 10 Effect of machine learning model for early warning of gas kick in deep-water drilling based on "Downhole-Riser-Wellhead" integrated monitoring

System workflow

The workflow of the early warning system for deep-water drilling gas kick is illustrated in Fig. 11. It consists of the following five technical components:

(1) data collection from sensors and composite drilling recorder;

(2) data transfer based on the Well Information Transfer Standard Markup Language (WITSML) transmission protocol;

(3) time sequence data storage, such as cloud computing;

(4) high-performance computing platform, such as workstations used to establish data-driven models;

(5) an early recognition system for deep-water drilling gas kick.

System architecture design

The system consisted of the following modules:

(1) Data Communication Module: Based on the TCP/IP network communication protocol, the Socket encapsulation interface was utilized to establish connections between the integrated logging instrument, the EKD equipment for precise monitoring, the PWD equipment for downhole pressure measurement, and the database.

(2) Data Storage Module: The Wellsite Information Transfer Standard Mark-up Language (WITSML) format was adopted to standardize and unify multi-source collected data from the comprehensive logging tool, EKD, and PWD, forming a WITSML data stream. The communication module synchronizes with the database, enabling the integration of real-time storage and monitoring data. The above parameters were displayed

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in the form of curves (unstructured data) for the convenience of on-site engineers and technical experts to observe parameter curves directly and intuitively.

(3) Early Warning: The core module of this system applied the real-time time sequence data mentioned above to the deployed "Deep-water Drilling Gas Invasion Early Warning Model," enabling early recognition of deep-water drilling gas kick. The gas kick alert signals captured during the monitoring process were transmitted to the audio-visual alarm system through serial communication, enabling the release of alarm information. Moreover, the system could notify various levels of personnel through emails, text messages, WeChat, and other forms of communication when encountering difficulties in the field. It was based on the established database of leaders, experts, and technical personnel, enabling cross-regional and cross-professional incident joint consultations. It also allows remote synchronous decision-making on offshore platforms, land bases, and headquarters.

(4) Well Control Strategy Module: This module included two sub-modules, "Pressure Control" and "Well Control Design." For moderate to low risk of influx, "Pressure Control" was carried out by converting to a controlled pressure drilling method, increasing pump discharge, and other measures. For high risk of influx, "Well Control Design" was conducted. It included the optimization of cyclic mud weight, calculation of pump-in heavy mud stroke count, determination of drilling fluid flow procedure using the drilling master method, and establishment of emergency shut-in well control measures.

(5) Auxiliary Function Module: This module was designed to enhance user experience and make it easier to use. It included four sub-modules: "Data Replay," "Assisted Calculation," "Help Instruction," and "Safe Exit." The "Data Replay" sub-module allowed users to replay historical data such as comprehensive drilling, EKD parameters, and PWD parameters based on the time interval selected by the user. It also enabled in-depth analysis of the root cause of gas kick, saved and printed historical curves. The "Assisted Calculation" sub-module mainly performed additional calculations such as conversion between imperial and metric units. The "Help Instruction" sub-module included information such as system owner, system developer, completion time, system version, system introduction, system manual, fundamental model explanation, and system usage regulations. The "Safe Exit" sub-module implemented a safe exit function for the system.

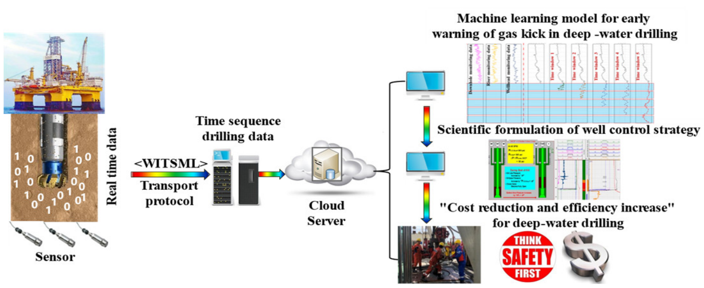

Fig. 11 Workflow of early warning system for gas kick in deep-water drilling (Yin et al., 2020)

System development content

The development of the early warning system for deep-water drilling gas kick includes three layers in Fig. 12: the application layer, the service layer, and the data layer (Yin et al., 2021). The application layer performs early warning of gas kick based on time sequence data filtered. The service layer implements the visualization of stored data and prediction results based on WITSML standards and TCP/IP protocols. The data layer uses Microsoft SQL Server 2008 database management system, employs object-oriented development techniques, and implements data calling and result storage. It mainly includes real-time drilling data, well-recording data, early warning prediction results of gas kick, records of well control measures, pre-input expert prior knowledge, system login information, etc. It enables functions such as query, modification, addition, and deletion.

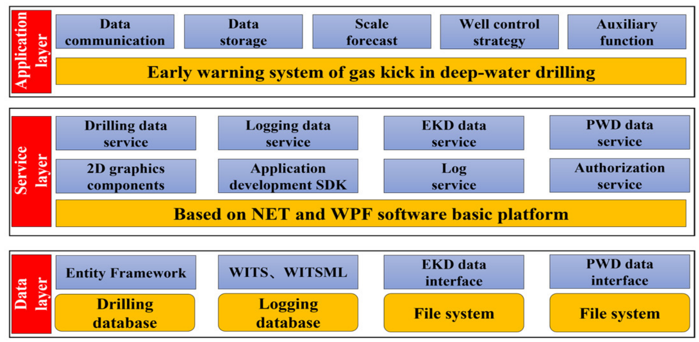

Fig. 12 Development content of early warning system for gas kick in deep-water drilling

CONCLUSIONS

(1) A short new side-bypass pipe in riser forms an independent channel for fluid flow. It effectively solves the problem of signal distortion caused by the rotation of drilling rods in conventional Doppler monitoring outside the riser.

(2) The "Downhole-Riser-Wellhead" integrated monitoring method eliminates the traditional monitoring delay and inaccuracy problem at the wellhead mud pit.

(3) The key to establishing an early warning machine learning model is to choose a neural network algorithm that is suitable for the deep-water drilling gas kick long-term sequence and the double-feature fusion of multi-level, multi-layer, and multi-source data.

(4) Implementing an early warning machine learning model for deep-water drilling gas kick can lead to an innovative shift from the current "real-time alarm" to "early warning" and provide sufficient time window for well control strategy formulation.

(5) Constructing a loss function to measure the difference between the results of complex and simplified machine learning models in early warning systems can effectively guide the training of the simplified model. This provides technical support for an early warning system for deep-water drilling gas kick that is highly timely and resource-efficient under real-world constraints.

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