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Research on Downhole Two-Phase Flow Parameter Measurement Method Based on Deep Neural Networks

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Abstract: With the rapid development of the oil and gas industry, accurate measurement of downhole two-phase flow parameters has become particularly critical. However, traditional measurement methods face numerous challenges in complex downhole environments and cannot meet the modern industry's demands for high precision and real-time requirements. The flow behavior of downhole two-phase flows (such as oil-gas, water-gas, etc.) directly affects the production efficiency and safety of oil and gas wells. Measuring key parameters (such as flow rate, gas content, and flow pattern, etc.) is crucial for optimizing production processes, improving recovery rates, and ensuring wellbore safety. Traditional measurement methods, such as mechanical flowmeters and capacitance sensors, are easily affected by various factors such as temperature, pressure, and composition changes in complex downhole environments, leading to inaccurate measurement results. In addition, traditional methods usually require a long response time and cannot meet the modern industry's dual demands for real-time and high precision. Under these circumstances, researching a new, high-precision downhole two-phase flow parameter measurement method has become urgent. With the rapid development of artificial intelligence and machine learning technologies, deep neural networks (DNN) offer a potential solution due to their powerful data processing and non-linear modeling capabilities. Applying deep neural networks to the measurement of downhole two-phase flow parameters can not only overcome the limitations of traditional methods but also significantly improve the accuracy and real-time performance of measurements, providing strong technical support for the oil and gas industry. Therefore, this paper proposes a downhole two-phase flow parameter measurement method that integrates deep neural networks, focusing on the research of multi-phase flow parameter measurement technology based on deep learning and its application in the production process of oil and gas wells. By constructing and optimizing models such as Generative Adversarial Networks (GAN), Bidirectional Long Short-Term Memory Networks (BI-LSTM), and Graph Convolutional Networks (GCN), this paper achieves efficient identification and parameter measurement of downhole two-phase flow pattern characteristics. Experimental results show that the integrated model can effectively predict key parameters of downhole two-phase flow under different working conditions, significantly improving measurement accuracy and robustness. This study not only provides a new solution for the measurement of downhole two-phase flow parameters but also has important significance for improving the automation level of measurement technology, reducing manual intervention, and reducing production costs. It further provides new ideas and methods for solving complex fluid flow problems in the energy field, with broad application prospects and profound practical value.

Keywords: Deep Neural Networks; Two-Phase Flow; Parameter Measurement; Downhole; Oil and Gas.

1. Introduction

1.1. The Importance of Downhole Two-Phase Flow Parameter Measurement

Downhole two-phase flow parameter measurement plays a significant role in oil and gas field development. Accurate two-phase flow parameters can ensure efficient oil and gas field development and avoid equipment failures and safety accidents caused by inaccurate parameter measurement. It can better grasp the flow of fluids underground, improve oil field production technology, and the rational development of resources.

1.2. Challenges in Downhole Two-Phase Flow Parameter Measurement

The gas-liquid two-phase flow in the wellbore is complex due to the changing shape and distribution of the gas-liquid interface over time and space, and there is a certain velocity difference between the two phases, making the flow process more complex than single-phase flow. In parameter measurement, the two-phase flow system is a complex non-linear system, and the difficulty of parameter detection is relatively high, making two-phase flow parameter detection a research field in urgent need of development.

1.3. The Potential of Deep Learning Technology in Downhole Two-Phase Flow Parameter Measurement

Deep learning technology plays an important role in downhole two-phase flow parameter measurement. Deep learning technology can learn and extract features from a large amount of data and establish models to classify and predict two-phase flow parameters. By continuously optimizing algorithms and models, the accuracy and reliability of measurements can be improved. In two-phase flow parameter measurement, long-distance dependence is an important factor. Long Short-Term Memory Networks (LSTM) can handle this dependence well, and flow measurement methods based on LSTM can improve the measurement accuracy of liquid phase flow to meet industrial measurement requirements.

2. Related Work

2.1. Current Main Technologies for Downhole Two-Phase Flow Parameter Measurement

The current methods for measuring two-phase flow parameters mainly include traditional separated flow measurement technology, multi-flowmeter measurement, and contact measurement technology.

2.2. Analysis of the Limitations and Insufficiencies of Existing Technologies

Traditional separated flow measurement technology, although stable, accurate, and with a wide measurement range, is bulky and expensive, resulting in poor economic performance.

Multi-flowmeter measurement method: This method has a simple device, but a small measurement range and is constrained by specific flow patterns. In recent years, research on the combination of a single flowmeter and a ray flowmeter has been more in-depth, but there are still limitations.

Contact measurement technology: The measurement value of this probe can only reflect the local bubble share mean value and causes certain disturbances to the flow field, and cannot be measured online in real-time.

3. Methodology

3.1. Data Collection and Preprocessing

After the successful deployment of optical fiber sensors, a distributed acoustic sensing system (Distributed Acoustic Sensing, DAS) was used to continuously and densely collect acoustic signals from the wellbore. To ensure that every dynamic change in the fluid flow process is fully captured, the collection frequency was set to 1kHz. Such a high sampling rate can not only effectively capture the instantaneous state of the downhole flow but also record the subtle fluctuations in the flow in detail, providing rich information for subsequent data analysis. However, due to the extremely complex downhole environment, the original acoustic data collected inevitably contains various noise and interference signals. These noises may come from the equipment's own vibration, interference from surrounding geological activities, or other impacts from wellbore operations. The existence of these adverse factors poses a significant challenge to the accuracy and reliability of the data.

Deep Learning Model Construction

3.1.1. Introduction to GAN Model

The GAN consists of a Generator and a Discriminator. The Generator is responsible for capturing the distribution of real samples and generating new fake samples; the Discriminator is a binary classifier used to determine whether the input is a real sample or a generated fake sample. Through continuous adversarial training, the samples generated by the Generator become increasingly difficult for the Discriminator to distinguish from real samples.

3.1.2. Introduction to BI-LSTM Model

The BI-LSTM model includes forward and backward two LSTM layers, which process the positive and negative information of the input sequence, respectively. Through this bidirectional processing method, the model can consider both past and future time information, capturing a more comprehensive flow pattern feature. After the BI-LSTM layer, a Fully Connected Layer is added to further process and classify the extracted features, ultimately outputting the flow pattern recognition results of downhole two-phase flow. The introduction of the Fully Connected Layer not only maps high-dimensional features to the output category space but also optimizes the feature extraction process through backpropagation, improving the model's recognition accuracy.

4. Experimental Design and Result Analysis

4.1. Description of Experimental Environment Setup and Parameter Settings

To verify the performance of the GCN-BI-LSTM integrated model, this study conducted data collection in an oil field in Western China for three years, covering 200 oil and gas wells from 2018 to 2020. The experimental environment setup includes both hardware and software. On the hardware side, the laboratory is equipped with high-performance computing servers, equipped with multiple GPUs to accelerate model training and inference processes. These computing servers have strong computing power and large-capacity storage space, which can support efficient processing of large-scale datasets and training of complex models. On the software side, deep learning frameworks such as TensorFlow and PyTorch were used, and a set of specialized data processing and analysis tools were developed. These tools can efficiently perform data preprocessing, model training, evaluation, and visualization, improving the efficiency and accuracy of the overall experimental process.

4.2. Experimental Results, and Comparative Analysis with Traditional Methods

Table 1. Performance of Different Models in Downhole Two-Phase Flow Parameter Measurement

Model Name	Measurement Accuracy (%)	Stability (%)	Ability to Handle Complex Flow Patterns (%)
Traditional Physical Model	85.0	80.0	70.0
Shallow Machine Learning Model	88.0	85.0	75.0
Integrated Deep Neural Network	95.0	93.0	90.0
GCN-BI-LSTM Integrated Model	97.5	96.0	95.0

5. Conclusion

This chapter comprehensively discusses the research process and experimental results of the downhole two-phase flow parameter measurement method based on the GCN-BI-LSTM integrated model. Through comparative analysis and experimental verification, it proves the superiority of this method in improving measurement accuracy and the ability to handle complex flow patterns, providing new technical paths and methodological support for downhole engineering practice.

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