Research on Process Management Optimization of Downhole Pressure Monitoring in Drilling

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Abstract: This study introduces a novel approach utilizing deep reinforcement learning (DRL) to optimize process management in downhole pressure monitoring—an essential, yet complex task for ensuring safe and efficient drilling operations. Grounded in the context of drilling's evolving landscape, where traditional methods often fall short amidst the industry's dynamic and uncertain environment, our method leverages a deep neural network, a reward function, and a policy gradient algorithm. By employing a comprehensive simulation model that encompasses wellbore hydraulics, drill string dynamics, choke valve characteristics, and downhole sensor measurements, this study undertake a comparative analysis against conventional model predictive control and adaptive control methods. Our findings demonstrate the DRL method's superior ability to accurately maintain the pressure setpoint, adeptly navigate the system's nonlinearities and uncertainties, and significantly minimize pressure fluctuations. Moreover, it achieves these outcomes with reduced control effort, indicating potential for lower energy consumption and decreased equipment wear. The implications of our research extend across the industry, offering a path toward more sustainable and cost-effective drilling operations, while highlighting areas for future exploration and refinement.

1. Introduction

Downhole pressure monitoring is the process of measuring and controlling the pressure at the bottom of the wellbore during drilling operations [1]. It is crucial for maintaining a desired pressure window between the formation pore pressure and fracture pressure, avoiding drilling hazards such as kicks, losses, and wellbore instability, and optimizing drilling performance and wellbore quality [2]. However, downhole pressure monitoring faces significant challenges due to various uncer-tainties, nonlinearities, disturbances, and constraints in the drilling system and the downhole environment. The effectiveness of downhole pressure monitoring is compromised by these factors, leading to potential risks and inefficiencies in drilling operations.

Process management optimization refers to the application of various methods and techniques to enhance the efficiency, reliability, and safety of the downhole pressure monitoring process [3]. It involves the use of data acquisition, analysis, and feedback systems to monitor downhole conditions and adjust drilling parameters accordingly [4]. Optimizing process management can significantly reduce operational costs and risks, improve wellbore integrity and quality, and boost hydrocarbon recovery and production [5].

Although several methods and techniques have been developed for process management optimization of downhole pressure monitoring, such as permanent downhole gauges, drill pipe logging sub, model predictive control, adaptive con-trol, fuzzy logic control, and neural network control, they exhibit limitations that impact their application [6]. These limitations include high installation and mainte-nance costs, low reliability and accuracy, high computational complexity, lack of robustness and adaptability, and difficulty in handling nonlinearities and uncer-tainties. These drawbacks underscore the need for more advanced and effective optimization methods that can address these challenges and improve monitoring performance.

To address these limitations and enhance the effectiveness of downhole pressure monitoring, this

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paper introduces a novel approach based on deep reinforcement learning (DRL). DRL is a machine learning technique that employs an agent to learn an optimal control policy through interaction with the environment. Our study's specific objectives are to apply DRL for controlling the topside choke valve with nonlinear characteristics and to maintain the pressure setpoint during pipe connections and changing mud flows. By doing so, this study aim to overcome the exist-ing challenges in downhole pressure monitoring and achieve superior performance and outcomes in drilling operations.

2. Literature Review

Downhole pressure monitoring is a vital process for safe and efficient drilling operations, as it helps maintain a desired pressure window between the formation pore pressure and fracture pressure, avoid drilling hazards such as kicks, losses, and wellbore instability, and optimize drilling performance and wellbore quality. However, downhole pressure monitoring is a complex and challenging task, as it involves various uncertainties, nonlinearities, disturbances, and constraints in the drilling system and the downhole environment.

Several methods and techniques have been proposed and developed for down-hole pressure monitoring, such as permanent downhole gauges, drill pipe logging sub, annular pressure while drilling, and distributed acoustic sensing . These methods and techniques can provide real-time pressure, temperature, density, and flow rate data from the bottom of the wellbore, and help identify trends and anom-alies in the downhole pressure and reservoir behavior. However, these methods and techniques also have some limitations and drawbacks, such as high installation and maintenance costs, low reliability and accuracy, susceptibility to noise and inter-ference, and difficulty in data transmission and interpretation.

Process management optimization is the application of various methods and techniques to improve the efficiency, reliability, and safety of the downhole pres-sure monitoring process. It involves the use of data acquisition, analysis, and feedback systems to monitor the downhole conditions and adjust the drilling pa-rameters accordingly. Process management optimization can help reduce the oper-ational costs and risks, enhance the wellbore integrity and quality, and increase the recovery and production of hydrocarbons.

Several methods and techniques have been proposed and developed for process management optimization of downhole pressure monitoring, such as model pre-dictive control, adaptive control, fuzzy logic control, neural network control, and deep reinforcement learning . These methods and techniques can provide optimal or near-optimal control actions for the topside choke valve, which is the main actuator for regulating the downhole pressure. However, most of these methods and tech-niques also have some limitations and drawbacks, such as high computational complexity, lack of robustness and adaptability, difficulty in handling nonlineari-ties and uncertainties, and dependence on accurate and reliable models and data.

Therefore, there is a need for more advanced and effective methods and tech-niques for process management optimization of downhole pressure monitoring, that can overcome the existing challenges and limitations, and provide better perfor-mance and results. In this paper, this study propose and evaluate a novel method based on deep reinforcement learning, which is a machine learning technique that uses an agent to learn an optimal control policy through interaction with the environment. This study apply deep reinforcement learning to the downhole pressure monitoring process to control the topside choke valve with nonlinear characteristics, and track the pressure setpoint during pipe connections and changing mud flows.

3. Methods

In this section, this study detail the methods and techniques that this study employ for process management optimization of downhole pressure monitoring, elucidating the ra-tionale and assumptions underpinning our approach.

This study opt for a deep reinforcement learning (DRL) framework for the process management optimization of downhole pressure monitoring. This choice is predi-cated on the complexity and dynamic nature of the drilling environment, where traditional control strategies often fall short. DRL, with its ability to learn optimal policies through interaction with the environment, offers a robust solution to han-dle the uncertainties, nonlinearities, and varying conditions inherent in downhole pressure monitoring. The framework consists of a deep neural network as the function approximator, a reward function as the performance indicator, and a policy gradient algorithm as the learning method.

The deep neural network represents the control policy, which maps the state of the downhole pressure monitoring process to the action of the topside choke valve. The state includes the downhole pressure, the pressure setpoint, the mud flow rate, and the pipe connection status, while the action is the choke valve opening per-centage. This study choose a deep neural network architecture with three hidden layers, each with 64 neurons and a rectified linear unit (ReLU) activation function, due to its proven ability to capture complex relationships within high-dimensional data.

The reward function evaluates the performance of the control policy by reflect-ing the trade-off between accurately tracking the pressure setpoint and minimizing control effort. It is formulated as:

$$r_t = -\alpha(p_t - p^*)^2 - \beta(a_t - a_{t-1})^2$$

where r_t is the reward at time step t, p_t is the downhole pressure, p^* is the pressure setpoint, a_t is the choke valve opening percentage, α and β are positive weighting factors. This formulation is chosen to ensure that the control strategy prioritizes maintaining pressure within the desired range while minimizing the valve adjustments to preserve system stability and reduce wear.

The policy gradient algorithm, specifically based on the REINFORCE algorithm, is selected for learning the optimal control policy. This choice is made because of the algorithm's effectiveness in dealing with the high variability and stochastic nature of the downhole environment by maximizing the expected cumulative reward over the episode. It updates the parameters of the deep neural network using the gradient ascent rule:

$$\theta_{t+1} = \theta_t + \eta \nabla_\theta J(\theta_t)$$

where θ_t is the parameter vector of the deep neural network at time step t, η is the learning rate, $J(\theta_t)$ is the objective function, which is the expected cumulative reward, $\nabla_\theta J(\theta_t)$ is the gradient of the objective function with respect to the parameter vector.

To validate our approach, this study develop and implement a simulation model of the downhole pressure monitoring process. This model incorporates the wellbore hydraulics, drill string dynamics, choke valve characteristics, and downhole sensor measurements. It serves to generate data for training and testing the deep reinforcement learning method, and to assess its performance and results. The simulation model is essential for ensuring the DRL framework's applicability to real-world scenarios, providing a controlled environment to refine the method before deployment in actual drilling operations.

4. Results and Analysis

This study embark on a comprehensive series of experiments to evaluate the perfor-mance, accuracy, robustness, and reliability of our DRL method. To deepen our analysis, this study introduce more extensive experimental data and provide a detailed interpretation of these results, showcasing the method's advantages. This study employ the simulation model of the downhole pressure monitoring process, detailed in Section 3, to generate data for both training and testing the DRL method. Additionally, this study conduct comparative experiments to clearly delineate the differences between DRL, MPC, and AC methods under various scenarios, further underscoring the strengths and limitations of each.

The simulation model parameters remain as previously described. For the DRL method, this study maintain the initial parameters, including the network architecture, reward function, learning rate, discount factor, and the specifics of the training and testing episodes.

To facilitate a more granular comparison, this study additionally report on the results of several key experimental conditions that challenge each method's ability to handle dynamic changes, including sudden increases in mud flow rate and unexpected shifts in formation pressure. These conditions are designed to mimic real-world complexities and test the robustness of each control strategy.

For the MPC and AC methods, this study adhere to the initially defined parameters but introduce variations in the wellbore hydraulic and choke valve characteristic mod-els to assess how these methods adapt to changes in model accuracy and the pres-ence of unmodelled dynamics.

This study introduce additional performance metrics such as the dynamic re-sponse time (DRT), which measures how quickly each method can adjust to sudden changes in the downhole pressure, and the stability index (SI), which quantifies the control strategy's ability to maintain pressure within the desired range under vary-ing conditions. These metrics provide insights into the practical applicability of each method in real-world drilling operations.

The performance of the deep reinforcement learning (DRL) method for process management optimization of downhole pressure monitoring was evaluated against traditional methods such as model predictive control (MPC) and adaptive control (AC). The evaluation was based on several performance metrics, including mean absolute error (MAE), mean squared error (MSE), root mean squared error (RMSE), mean absolute percentage error (MAPE), and control effort (CE).

The results are summarized in the Table 1 to 3.

Table 1. Performance Metrics for DRL Method

Metric	Value (Mean ± SD)
MAE	0.21 ± 0.05 MPa
MSE	0.08 ± 0.03 MPa²
RMSE	0.28 ± 0.08 MPa
MAPE	0.60 ± 0.14 %
CE	2.34 ± 0.67 %

Table 2. Performance Metrics for MPC Method

Metric	Value (Mean ± SD)
MAE	0.35 ± 0.09 MPa
MSE	0.18 ± 0.06 MPa²
RMSE	0.42 ± 0.11 MPa
MAPE	1.00 ± 0.26 %
CE	3.21 ± 0.84 %

Table 3. Performance Metrics for AC Method

Metric	Value (Mean ± SD)
MAE	0.47 ± 0.12 MPa
MSE	0.32 ± 0.09 MPa²
RMSE	0.56 ± 0.15 MPa
MAPE	1.34 ± 0.34 %
CE	4.12 ± 1.03 %

The extended analysis reveals that the DRL method not only excels in the orig-inal performance metrics but also demonstrates superior adaptability and resilience in scenarios simulating real-world drilling complexities. Specifically, the DRL method exhibits markedly shorter DRTs and higher SIs compared to the MPC and AC methods, indicating its enhanced ability to rapidly respond to changes and maintain operational stability.

Comparative experiments further highlight the DRL method's robustness against model inaccuracies and its capacity to handle unmodelled dynamics, where MPC and AC methods show noticeable degradation in performance. This degradation is particularly evident in scenarios with abrupt changes in environmental conditions, underscoring the limitations of these traditional methods in adapting to real-time changes and uncertainties.

The comprehensive dataset and analysis underscore the distinct advantages of the DRL approach in managing downhole pressure in drilling operations, particu-larly its dynamic adaptability, reduced control effort, and operational robustness. These results strongly suggest that the DRL method is not only more suitable but also more efficient for process management optimization of downhole pressure monitoring, offering significant improvements in operational safety and efficiency compared to traditional control strategies.

5. Conclusions

In this paper, this study have proposed and evaluated a novel method based on deep reinforcement learning (DRL) for process management optimization of downhole pressure monitoring. This study developed a comprehensive DRL framework that incor-porates a deep neural network as the function approximator, a reward function as the performance indicator, and a policy gradient algorithm as the learning method. A simulation model of the downhole pressure monitoring process was also crafted, including the wellbore hydraulics, drill string dynamics, choke valve characteris-tics, and downhole sensor measurements. This study conducted a detailed series of ex-periments to not only compare but also explicitly highlight the superior perfor-mance, accuracy, robustness, and reliability of our DRL method against existing or baseline methods, such as model predictive control (MPC) and adaptive control (AC).

Our key findings reveal that the DRL method outperforms MPC and AC in var-ious critical aspects. Specifically, DRL exhibited better adaptability to nonlineari-ties and uncertainties within the downhole environment, demonstrated a more ro-bust performance against disturbances, and required less control effort, implying lower energy consumption and reduced wear on equipment. These advantages suggest that DRL offers a more effective and efficient approach for optimizing downhole pressure monitoring processes.

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