Intelligent MPD Set-Point Control for Narrow Windows: A Reinforcement Learning Framework for Automated Choke Control in Deepwater HPHT Wells

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ABSTRACT

Deep water high-pressure, high-temperature (HPHT) drilling in managed pressure drilling (MPD) offers great challenges because of very thin changes between pore pressure and fracture gradient, frequently below equivalent mud weight of 0.3 ppg. Traditional rule-based MPD tuning algorithms fail to hold optimal setpoints in real-time resulting in influx/loss events and inefficient rate of penetration (ROP).

This paper introduces a new reinforcement learning (RL) model of intelligent MPD set-point control, which is more specifically backpressure and equivalent circulating density (ECD) optimization in narrow-margin deepwater wells that characteristic of the Gulf of Guinea area, such as Ghana and Nigeria. A Deep Deterministic Policy Gradient (DDPG) model was optimized using past MPD operational data in West African deepwater campaigns which included a multi-objective reward function balancing between influx risk, loss risk, and ROP optimization. The paradigm shows that the pressure control accuracy (23% improvement over rule-based approaches) and mean absolute pressure deviation (42 psi to 32 psi) are lower in comparison to rule-based approaches.

Moreover, the model had an average increase of 15 percent in the average ROP and was able to keep wellbore stable despite the thin drilling window. The intelligent control system detected and reacted to simulated kick situations 18 seconds earlier than the traditional automated MPD systems, which is a giant development in real-time well control capacity. The above results imply that the operational benefits of RLbased MPD control are enormous in strenuous deepwater HPHT drilling operations, and could be applicable to the whole range of the Gulf of Guinea deepwater drilling ventures.

Keywords: Managed pressure drilling, reinforcement learning, HPHT, narrow margin, deepwater drilling, DDPG, choke control, Gulf of Guinea

INTRODUCTION

The world chase of the hydrocarbon resource has moved drilling activities towards the deepwater environment with intense geology such as the high-pressure, high-temperature (HPHT) oil reservoirs with small working conditions. These issues are seen in the Gulf of Guinea, which contains the prolific hydrocarbon provinces offshore Nigeria and Ghana, and the deepwater operations have added significant production capacity to the region. The deepwater fields in Nigeria have a record of contributing more than 800,000 barrels per day to national production with Ghana having the Jubilee, TEN and Sankofa fields that contribute around 160,000 barrels per day by the deepwater offshores.

The main problem with HPHT deepwater drilling is that formation pore pressure and fracture gradient have a thin margin that may not exceed 0.3 ppg equivalent mud weight (EMW). This limitation is a serious hindrance to the operational time frame to ensure stability of drilling wellbores besides maximizing the performance of the drilling. The pressure margin between pore pressure and fracture initiation pressure determines the margin of drilling; when the equivalent circulating density (ECD) reaches any of the above limits, then influx or loss

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situations can take place. Traditional drilling techniques are often inadequate in addressing such thin margins of pressure as they are incapable of delivering the accuracy that is necessary in real-time management of pressure.

The making of managed pressure drilling (MPD) has become the supporting technology in overcoming such hazardous conditions. In all its drilling activities, MPD makes use of dynamically controlled surface equipment such as choke valves and auxiliary pumps to ensure total control of the bottomhole pressure (BHP). The method allows the real-time management of the pressure, limiting the potential influx and loss circulation and permitting the drilling works to be performed in the previously undrillable formations. The performance of MPD operations is however critical on the accurateness and responsiveness of the set-point control system controlling the position of choke and application of the backpressure.

Current MPD control systems are primarily based on proportional-integral-derivative controllers or model predictive control systems that are based on simplified models of hydraulic systems Although these methods have proven to be very successful in numerous applications, it is limited in very dynamic HPHT environments where formation pressures are very dynamic in terms of ramps and regressions. The complexity of the natural multi-phase flow process, the fluid's dependent properties on temperature, as well as the variations in the wellbore conditions are in question of the accuracy of the reduced-order models on which conventional controllers are based. Moreover, rule-based tuning methods demand a lot of manual tuning, and are not able to react to dynamic downhole conditions dynamically.

The recent development in artificial intelligence, especially reinforcement learning (RL) has provided good alternative solutions to the complex control problems in the drilling activities. Deep RL algorithms have shown an impressive ability in optimization of drilling parameters such as weight on bit (WOB) and rotary speed (RPM) to optimize ROP without causing downhole vibrations. The Deep Deterministic Policy Gradient (DDPG) algorithm, which is algorithmically tailored to continuous action space, has been demonstrated to be of special interest to drilling tasks in which the outputs of control systems need to be continuously tuned, as opposed to being chosen between discrete values. The given research fills an important gap in the literature by creating and testing a reinforcement learning model that is specifically tailored to MPD set-point control in narrow-margin HPHT deepwater wells. The paper is dedicated to the Gulf of Guinea working situation, where historical data on the Nigerian and Ghanaian deepwater campaigns is used to develop models that suggest realtime backpressure and equivalent mud weight set-points. The new multi-objective reward function proposed also balances influx risk, loss risk and ROP optimization simultaneously, unlike previous single-objective based research which has dominated the research on the automation of drilling.

The three main goals of the study are as follows: first, this paper is expected to create a DDPG-based control agent that will be able to learn the optimal MPD set-point policies on the basis of historical operational data; second, this paper is supposed to show the quantifiable benefits of pressure control accuracy and drilling performance that are provided by the framework in comparison with the rule-based approaches to MPD tuning; and third, this paper should prove that the framework will be able to detect early kicks and respond during simulated HPHT conditions typical of the Gulf of Guinea conditions.

LITERATURE REVIEW

Managed Pressure Drilling in HPHT Environments

Managed pressure drilling is a modern technology that was aimed at solving the difficulty of drilling in HPHT reservoirs often encountered in deepwater conditions. The technology offers accurate annular pressure profile controlling by manipulating surface backpressure using automated choke systems to give operators the capability of maintaining constant bottomhole pressure (CBHP) within narrow operational windows. The basic principle is to seal the annulus with a rotating control device (RCD) and supply flow via a choke manifold to permit the quick pressure up and down adjustments to counter any changes in ECD needed during various operations of the drill.

The use of MPD in deepwater HPHT environment has been well reported with significant achievements in the Mediterranean, West Africa and Southeast Asia. The application of MPD in the West Nile Delta by BP proved that drilling in less than 0.3 ppg EMW PP-FG window formations was possible at target depth, and that the technology would allow it to obtain wells that could not have been reached by conventional techniques. On the same note, the breakthrough of ENI through its continuous circulation technology coupled with MPD also facilitated successful penetration through ultra-narrow pressure windows of deepwater HPHT conditions. These case studies can define MPD as a developed technology which can cope with extreme challenges in drilling but also mark the importance of correct pressure control and the drawbacks of available automation solutions.

Control Systems for MPD Operations

The automation process has been developing over the last twenty years in the system of the MPD choke control as it shifted to the period of the manual control systems to the modern system of the model-based control. Most modern MPD control systems use hydraulic models to calculate real time downhole pressure and feedback control algorithms to automatically set choke position to achieve desired pressure set-points. Model predictive control has become the most popular way of automated MPD operations through the capacity to deal with numerous inputs and outputs without violating operational constraints. The initial application of a highly accurate real-time high-fidelity flow model modified to operate in an MPC controller was reported by Park et al. (2020), in which the model showed a better control outcome when used in the process of drilling, pipe connections, and mud density displacements. The research has pointed out that the success of controllers is dependent on the outlook of the model, and discrepancies between the model and the real system results in poor control.

It has been suggested that nonlinear MPC (NMPC) strategies are required to deal with nonlinearities inherent to MPD systems, especially when operating in two-phase flow conditions which appear when there is a kick event. The Memorial University researchers have come up with elaborate solutions of simple PID controllers to complex NMPC with fault management capabilities, which have been experimented both at the simulation and lab level. Despite this progress, there is still much work to be done before robust control performance can be attained throughout the complete range of conditions experienced in HPHT deepwater drilling, and especially during transient periods of operations, such as during connections, trips, and formation transitions.

Machine Learning Applications in Drilling

Machine learning applications have proved to be very successful in other drilling applications that include prediction of ROP, estimation of ECD, and optimization of drilling parameters. Gamal et al. (2021) used artificial neural networks (ANNs) and adaptive network-based fuzzy inference systems (ANFIS) to predict ECD with correlation coefficients of more than 0.96 and average error ratios of less than 0.7 on average. Recently, Ekechukwu et al. (2024) introduced an explainable machine learning framework based on XGBoost methodology to predict ECD and showed R 2 values of 0.989 to predict the trend on testing data with a feature importance analysis to interpret the results. Such studies prove that machine learning models are able to effectively represent the multifaceted relationships between drilling parameters and the most important wellbore conditions.

Random Forest models have demonstrated especially good performance in ECD prediction with the authors showing R^2 of 0.9859 and RMSE of 0.0017 in testing datasets with input of parameters of surface drilling (Gao et al., 2024). The benefit of surface measurements only removes the use of expensive downhole sensors yet still has a high prediction accuracy. These methods can be immediately applied to MPD control systems and, in that case, the reliable ECD estimation is required to keep the pressure within tight operational limits.

Reinforcement Learning for Drilling Optimization

Reinforcement learning is a new paradigm to the automation of drilling, which promises the possibility of agents learning how to act in the best control policy when interacting with their surroundings instead of being programmed to do so. For instance, a virtual drilling agent developed by Huang et al. (2024) is based on DDPG algorithm and will automatically optimize drilling variables, incorporating ROP, vibration, dull bit, and risk of tool breakage into a reward function. Their findings indicated that RL model has the potential of identifying the

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best solution to different drilling conditions including hard formation, embedded rock and unstable drilling conditions.

The DDPG algorithm belongs to the type of actor-critic algorithms for RL, which combines value-based and policy-based approaches for dealing with actions that have infinite dimensions. The algorithm keeps two neural networks, an actor network which computes the best action based on the current state, and a critic network which approximates the value of state-action pairs. This is particularly suited to MPD control systems wherein the set-points for choke position as well as backpressure are not chosen discretely but are varied continuously.

Keshavarz et al. (2024, 2025) suggested deep reinforcement learning representations of the real-time planning of drilling operations with Markov Decision Process formulations and the application of the Gaussian process algorithm to determine the safe operating window. Their work showed that in the process of wellbore cleaning, automated decision-making was possible, the high-level performance could be ensured, and non-value-added tasks are removed. The theoretical use of RL methods in the MPD set-point optimization is supported by the autonomous optimization technique created by the researchers utilizing the Q-learning algorithms to control the drilling parameters.

Research Gaps and Contribution

The research gaps and contribution are as follows. Although tremendous progress was achieved in the field of MPD automation and RL-based drilling optimization, there is an essential gap in the intersection. Existing systems of MPD control are mainly model-based and need good hydraulic models and manual fine-tuning. Although, RL methods have been used to optimise the drilling parameters (WOB, RPM) their implementation to MPD set-point control has not been investigated in the published literature. Moreover, the current RL drilling programs are mainly devoted to single-objective optimization (usually, the ROP maximization), whereas the MPD control should be considered in a multi-objective way and involve the influx risk, loss risk, and drilling efficiency optimization simultaneously.

This paper fills these gaps by creating a DDPG-based framework that has been tailored in MPD set-point control in narrow-margin HPHT wells. The new contribution consists of: (1) the MPD control problem is formulated as a continuous-action RL problem; (2) a multi-objective rewarding function balancing the risk of influx/loss and ROP maximization is developed; (3) the problem is trained and validated using data that is representative of Gulf of Guinea deepwater operations; and (4) the problem is quantitatively compared to rulebased MPD tuning techniques.

METHODS

Data Description and Preprocessing

The data used in this paper is operational data of 12 motorized HPHT wells that have been drilled in the Gulf of Guinea between 2018 and 2024, of which 7 wells are offshore Nigeria and 5 wells are offshore Ghana. The data were collected in the MPD operations carried out as per the CBHP methodology in water depths of 850 to 2,100 meters of which the depths were measured up to 5,500 meters. The total data size is about 18,500-time stamped records taken at 10 s when MPD is active.

The input features are measurements of the surface that are regularly taken when the MPD is being used: pump flow rate (GPM), standpipe pressure (SPP), weight on hook (WOH), rotary speed (RPM), rate of penetration (ROP), mud density (ppg), and choke position (%). The target variables in this work are bottomhole pressure as well as PWD tools and ECD from downhole measurements. Extra derived features would be flow-in/flowout differential, pressure trend derivatives and time-lagged variables that represent system dynamics.

Preprocessing of the data was done by the standard drilling data quality assurance. Values from null records, sensor malfunction, or redundant data points were dropped, making valid observations 15,840. Outlier detection and removal was done by the Interquartile Range (IQR) method, which removes about 4% of records that

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contained anomalies in the pressure or flow measurements. All features were normalized to a z-score to guarantee equal scaling of all the input dimensions, which is vital in the stability of neural network training.

Stratified sampling was used to divide the dataset into the training (70%), validation (15%), and testing (15%) subsets to maintain representative representation of well types and formation characteristics by the partitions. Each well was ordered in time to retain realistic sequential dependencies that are needed when training RL.

Reinforcement Learning Framework

The problem of MPD set-point control was defined as Markov Decision Process (MDP) that could be optimized by use of a RL. On every time step t, the agent perceives state s t which includes the current drilling parameters and pressure readings, chooses action a t which includes backpressure and ECD set-point changes, receives reward r t indicating the performance of control, and changes to successor state *s_{t+1}*.

State Space: The state vector $s\_t \in \mathbb{R}$ consists of pump flow rate, standpipe pressure, weight on hook, rotary speed, ROP, mud density, current choke position, current backpressure, BHP, ECD, formation depth, and porefracture margin (calculated based on offset well data).

Action Space: Action vector $a\_t \in \mathbb{R}^2$ defines continuous changes in: (1) backpressure set-point (0 +50 psi), and (2) desired ECD set-point (0 +0.02 ppg). The continuous action space is needed to obtain fine-grained control of pressure within tight margins that are typical of HPHT works.

Reward Function: The reward function was designed as a multi-objective to balance competing goals of MPD control:

$$r_t = w_1 \cdot r_{pressure} + w_2 \cdot r_{ROP} + w_3 \cdot r_{stability}$$

where:

- $r_{pressure} = -|\ BHP_t - BHP_{target}\,|/\sigma_{pressure}$ penalizes deviation from target BHP
- $r_{ROP} = (ROP_t - ROP_{baseline})/ROP_{baseline}$ rewards ROP improvements
- $r_{stability} = -\lambda_1 \cdot I_{influx} - \lambda_2 \cdot I_{loss}$ penalizes influx/loss indicators

Sensitivity analysis helped to optimize the weighting coefficients ($w_1 = 0.5$, $w_2 = 0.3$, $w_3 = 0.2$) in order to create a balanced optimization of objectives. The influx indicator *I_influx* activates when flow-out exceeds flow-in by more than 2%, while *I_loss* activates when the opposite condition holds for sustained periods.

DDPG Algorithm Implementation

The Deep Deterministic Policy Gradient algorithm was selected for its proven capability in continuous control tasks with high-dimensional state spaces. DDPG maintainsintains four neural networks: actor network μ(s|θ^μ), critic network Q(s,a|θ^Q), and their respective target networks with parameters θ^μ' and θ^Q' that are soft-updated to improve training stability.

The actor network architecture comprises three fully-connected layers with 256, 128, and 64 neurons respectively, using ReLU activation functions and batch normalization. The output layer employs tanh activation scaled to the action bounds. The critic network concatenates state and action vectors after the first layer, with subsequent architecture matching the actor.

Training utilized experience replay with buffer size 100,000 and mini-batch size 64. Target networks were updated using soft update coefficient $\tau = 0.001$. The Ornstein-Uhlenbeck process provided exploration noise with parameters $\theta = 0.15$ and $\sigma = 0.2$, decayed exponentially over training episodes. Learning rates were set at 10^{-4} for the actor and 10^{-3} for the critic, following recommendations for drilling applications.

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Baseline Comparison Methods

To quantify improvements over existing approaches, three baseline methods were implemented:

Rule-Based Control: Traditional MPD automation using PID controller with fixed gains tuned for nominal operating conditions. Backpressure set-points adjusted based on lookup tables indexed by measured depth and drilling phase.

Model Predictive Control: Linear MPC using simplified hydraulic model with prediction horizon of 40 time steps and control horizon of 15 steps. The parameters of bulk modulus and effective density used in the model are calibrated using initial well data.

Random Forest Regression: Machine learning control which employs RF model to predict BHP and calculates real-time set-point with respect to the predicted pressure variations. RF model was formed on the same partitions of data that was used in RL training.

Evaluation Metrics

The performance of the models was assessed based on the operational priorities and operational factors in MPD control:

- **Mean Absolute Pressure Deviation (MAPD):** The average of the absolute deviation of actual and target BHP in all time steps.
- **Pressure Excursion Rate (PER):** Percentage of the time steps in which BHP was out of bounds of safe drilling window limits.
- **Average ROP:** Mean drilling rate achieved during model control periods
- **Kick Detection Time (KDT):** Time elapsed between simulated kick initiation and control system response
- **Control Stability Index (CSI):** Standard deviation of choke position changes, indicating control smoothness

RESULTS AND DISCUSSION

Model Training and Convergence

The DDPG agent was trained in 2,000 episodes that included a whole drilling cycle of one well in the training set. The convergence of training was measured using cumulative episode reward and critic loss measures. The agent showed steady learning behavior; the average reward of the episode went up by -245 (random action at the start) to +128 (converged action) in about 1,200 consecutive episodes. The last episode (1,500) is the stabilization point of validation performance, which suggests that there is sufficient generalization but no overfitting.

Sensitivity analysis on the hyperparameters showed that the weights of the reward functions had a big impact on behavior learned. Increased w_2 (ROP weighting) resulted in aggressive policy that at times nearly touched the window walls, whereas conservative w 1 (pressure weighting) resulted in consistent but slower drilling.

The selected configuration ($w_1 = 0.5$, $w_2 = 0.3$, $w_3 = 0.2$) achieved optimal balance for HPHT narrow-margin conditions.

Pressure Control Performance

Metric	Rule-Based	MPC	RF Regression	DDPG (Proposed)
MAPD (psi)	42.3	38.1	35.7	32.4

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PER (%)	4.8	3.2	2.9	1.4
CSI (% change/step)	2.1	1.8	2.4	1.5

The DDPG model showed the best accuracy of pressure control based on all the evaluation measures on the held-out test. The absolute deviation in the mean pressure was also lowered by 23 percent relative to control using rules (42.3 psi versus 32.4 psi), which indicates a significant change in the accuracy of tracking of BHP. The rate of pressure excursion (indicating frequency of unsafe window violations) was found to reduce when using rule-based methods and DDPG by 4.8 to 1.4%, respectively, indicating a reduction of 71% in unsafe pressure excursions.

These increases are especially important with respect to the close drilling margins of Gulf of Guinea HPHT wells, in which the difference between pore pressure and fracture gradient could be below 0.3 ppg. In these limitations, minute deviations in accuracy of pressure control also result in significant decreases in the risk of influx/loss. The MPC base case delivered moderate results (MAPD = 38.1 psi), which is in line with the literature reports that simplified hydraulic models restrict the accuracy that can be obtained in highly dynamic environments.

Drilling Performance Optimization

The multi-objective rewarding method allowed the DDPG agent to achieve drilling performance and pressure regulation goals. Average ROP values in the test set were 15 percent greater than rule-based control (47.2 ft/hr vs. 41.1 ft/hr) without changing the rates of pressure excursions. This enhancement is in line with industry experience that MPD is a superior technique that facilitates the achievement of higher ROP through drilling with light mud weights and the usage of surface back pressure to sustain formation containment.

Evaluation of acquired control policies showed that the agent had learned complex drilling strategy depending on the conditions. During periods of stable formation the agent kept the lower backpressure at the lowest possible level to ensure the maximum ROP without compromising on the safety margins. The agent anticipatorily changed set-points before excursions occurred once he saw signs of formation pressure variations (increasing flow-out differential, pressure trends). This is a data-learned anticipatory behavior that is similar to the best practices used by seasoned operators of MPD and performs better with consistency and speed of reaction.

Kick Detection and Response

The test data was fed with simulated kick scenarios to test the responsiveness of the framework to influx events. The kick models are created based on step-wise increases in the rate of formation fluid influx. The models are tuned to provide the correct flow & pressure characteristics based on kick dynamics observed during MPD operations. The DDPG agent proved to be 18 seconds faster than rule-based control in kick detection response time (18 seconds vs. 34 seconds after the influx start to choke response). It is an increase due to the sensitivity of the agent to the minor pressure and flow indications that lead to evident kick patterns. Modern MPD systems have a component, the influx-loss detection, which detects the symptoms of downhole events before they turn into well control events. The DDPG model was successful in its attempt to recognize and react to these early signals and corrective action was taken at the incipient stage when control intervention was most effective.

Comparison with Related Work

The performance gains reported in this research are favorable to those reported in the corresponding applications of RL drilling. Huang et al. (2024) established that DDPG may be useful in an attempt to optimize drilling parameters (WOB, RPM) to maximize ROP without the occurrence of stick-slip vibrations. This is extrapolated to the more intricate domain of MPD control in the present work, in which real-time continuous pressure management has to strike a balance between various competing goals. The 23%, relative to the 10% performance gain of RL-based heave compensation control using DDPG, improvement in pressure control accuracy is indicative of the fact that the MPD control problem is one that RL optimization can address especially well.

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This could be an indication of the rich feedback contained in MPD systems, where pressure and flow metrics give instant feedback on the effectiveness of control actions, which makes learning effective policies.

Limitations and Practical Considerations

These results have a number of limitations that should be recognized during their interpretation. First, the dataset is a restricted sample of Gulf of Guinea operations, and it might not represent the range of conditions that might occur worldwide. The transfer learning techniques might be needed to adjust the trained models to significantly different geological contexts. Second, the simulation model though it is tuned to historical data does not capture all dynamic phenomena which are experienced during live drilling operations, especially the extreme events that are very rare. A real implementation of RL-based MPD control would involve a significant amount of validation, such as hardware-in-the-loop testing of real MPD equipment prior to field experiments. There are other implementation challenges in terms of integration with the current rig control systems, cybersecurity, and regulatory approval. Nevertheless, the performance gains illustrated indicate that further extension of the RL-based MPD control is worth earning serious consideration in the event of demanding deepwater operations.

CONCLUSION

This paper introduced a new reinforcement learning model to smart MPD set-point operation in narrow-margin deepwater HPHT wells, which is a significant deficiency in the sphere of automated drilling technology. The DDPG-based method showed a drastic change over traditional rule-based and model-based control strategies, whereby the mean absolute pressure deviation was reduced by 23 percent, the rate of pressure excursion was minimized by 71 percent, and the average ROP was improved by 15 percent on past historical operations of Gulf of Guinea. The multi-objective reward function design was critical in the process of balancing the competing needs of pressure control accuracy, drilling efficiency and well control safety inherent in the process of HPHT MPD operations. The trained control policies had advanced anticipatory behavior, sensing and responding to formation variations more rapid than the traditional systems and had less turbulent control measures that minimized equipment damage and complicated operations.

These results indicate that reinforcers learning can be of considerable value in developing MPD automation, especially in the harsh environment where the traditional methods fail to sustain optimal performance. The Gulf of Guinea area, which has a long history of deepwater drilling and further exploration and development, will be a perfect site to further development and field testing of intelligent MPD control systems.

The research opportunities in the future include: (1) to multi-well transfer learning to enable rapid adaptation to new drilling campaigns; (2) to physics-informed neural networks to enhance the interpretability of this model; (3) to ensemble RL to ensure the models are more robust; and (4) pilot testing in collaboration with operators that operate in West African deepwater basins. The combination of high levels of control technology and growing deepwater resources has placed the industry in a position to reach safely and efficiently resources in more challenging environments.

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