Misan Journal of Engineering Sciences ISSN-E: 2957-4250
Vol.5, No. 1, 28 June 2026 ISSN: 2957-4242

Under Balanced Technique to Enhance Drilling Operations

Amel H. Assi

Petroleum Engineering Department, College of Engineering, University of Baghdad, Baghdad, Iraq
**Corresponding author E-mail:* amel@coeng.uobaghdad.edu.iq

(Received 20 Aug 2025, Revised 31 Jan 2026, Accepted 31 Jan 2026)

Abstract: Underbalanced drilling (UBD) is a successful drilling technique that upholds well pressure purposefully lesser than formation pressure. This approach effectively permits reservoir fluids to flow inside the well throgh drilling, diminishing formation damage and meaningfully attractive hydrocarbon recovery. UBD signifies a standard shift from traditional drilling techniqe. It bring into line with the industry's growing suring on cost-effective, reservoir-friendly, and high-performance techniques. The correlation between Rate of Pentration (ROP) and UBD for several wells by drilling program is demonstrates the progressive development in drilling performance because of accrued experience, optimizing engineering design, and superior formation reaction under reduced bottom hole pressure. UBD obviously heightened ROP across the field likened to offset overbalanced wells, assistant its request in future progress phases. Effective and cost-effective of directional wells requires the execution of best drilling performs and progressive techniques to optimize drilling processes. Disappointment to sufficiently consider drilling risks can result in unproductive drilling processes and Non-Productive Time (NPT). The application of UBD be contingent on the mechanical stability of the drilled formation, among other issues. In over-all, poorly consolidated, depleted formations are not appropriate for that technology. Finally, the results show that underpressure drilling (UBD) is better than overpressure drilling (OBD) in the typical porous shale and limestone formations of the studied wells.

Keywords: Drilling ; Pressure; Formation; Density,Rate of Pentration

1. Introduction

Over Balanced Drilling(OBD) is the furthermost corporate drilling method; nevertheless, it has numerous disadvantages for instance mud losses,formation damage, and stuck pipes; challenges that are corporate in highly fractured formations and high permeability zones . However, to overcome those issues, UBD method could be implemented [1]. Khaled ,2020 assessed the possibility of UBD in mature iraqi oil fields, merging technical and economic investigates. It assessed altered reservoir conditions for determining the feasibility of UBD for reducing formation damage and enhancing production [2]. Salaheldin ,2019 presented a detailed review of foamed drilling fluids in UBD applications, deliberating operative challenges, benefits, and future progresses for improving well productivity [3]. Faisal,2021 presented a simulation model for UBD by using supercritical CO_2 as the drilling mud. his effort focused on pressure performance and fluid dynamics for enhancing safety and effectiveness [3]. Ali ,2018 pointed at making a decision-support system using fuzzy logic for assessing whether UBD is appropriate for specific wells, in view of geological and economic limits [4]. Fattah et.al ,2020 focusing on adapting UBD to chosed formations, assessing surface equipment requirements, geological circumstances, and safety observes [5].Bedjaoui 2017,discovered the performance of UBD tools in field trials across spesific formations. It demonstrated how UBD could reduce formation damage and enhance production rates [6]. David Simpson and Mark Pope ,2010 There comprehensive manual covers practical planning, operational procedures, and implementation of UBD across altered environments, comprising offshore applications [7].McGowen ,2008 investigated UBD's restrictions in extreme drilling circumstances and its limitations in both onshore and offshore surroundings [8].

DOI: https://doi.org/10.61263/mjes.v5i1.202

Medley et.al.,2011 investigated UBD's performance in horizontal drilling , with a focusing on reservoir properties and productivity [9]. Rosalvina ,2019 explored UBD's role in workover processes and the selection of well-matched production fluids for preventing formation damage [10]. Fred ,2018 Considered the practical request of UBD in global surroundings, terminating logistics, equipment, and performance outcomes [11].Sid ,2017 has recognized UBD's engineering strategy standards and safety code of behavior across numerous international processes. international tasks [12].Mohamed ,2013 deliberate the starring role of UBD in stimulating oil recovery from obviously fractured carbonate reservoirs and rextracting damage to fracture systems [13].Andersen, H., Vigrestad et.al ,2021 directed a comprehensive investigation of the efficiency of aerated drilling mud in meaningfully improving the Rate of Penetration (ROP) throughout UBD processes [14].Some studies made robust importance on hydraulic optimization and increasing operative effectiveness, representative the compelling compensations of accepting these original techniques for enhanced drilling act [15].Robert ,2016 Arrange the altered copy of UBD for tight gas surroundings, with a strong importance on maximizing safety, supervisory costs, and attractive productivity [16]. This planned emphasis will ensure optimal recital and profitability in stimulating conditions [17].Don ,2015 investigated the possipility of UBD using in offshore drilling, emphasizing safety considerations and pressure control responsibilities [18]. The incorporation of artificial intelligence (AI) into geoscience has altered subsurface characterization, principally in hydrocarbon investigation [19]. According to Bergen et al. (2019), that alteration began in earnest during the 2010s, powered by three key advances: (1) the obtainability of high-enactment cloud computing, (2) the arrival of open-source machine learning libraries identical TensorFlow and PyTorch, and (3) the growing volume of digitized well data from mature fields [20]. The major goal of this study is to improve a robust Python-based AI model capable of correctly guessing and rebuilding absent well log data, for instance Gamma Ray, triple combo logs, and resistivity logs. This initiative aims to improve data integrity, optimize drilling strategies, and maximize resource extraction.This effort assesses the use of non-linear regression techniqes for multivariate regulator of pressure and flow through UBD using a fit-for-determination relation roboust, as pressure and flow are the two most important factors in success. In petroleum engineering, "brittle formations" and "strong formations" refer to rock properties that affect drilling and production operations. Brittle formations are those that fracture easily under pressure, while strong formations are those that resist fracture by tested possible configurations for using UBD.

2. Methodology:

This study focused on the importance of using flow rate and pressure as two important factors in UBD. The intention is to target formations that are prone to loss of drilling cycle, stuck, cracked or fractured formations, how to deal with them, and which technique is better, UBD or OBD. By using Eq. 1,2 and 3. Random Forests have become particularly popular for ROP prediction due to their inherent feature importance quantification. Hall (2016) achieved MAE of 0.02 g/cc for density ROP prediction in the North Sea using 17 input data [21]. Linear regression remains the most widely used technique for log prediction due to its simplicity. However, this approach fails dramatically in complex lithologies like fractured carbonates where mineralogy dominates ROP responses . Geostatistical methods such as kriging and co-kriging improve upon simple regression by incorporating spatial correlations. Variogram-based kriging could reduce prediction errors by 15–20% compared to linear regression in channelized reservoirs. Collect comprehensive data from five oil wells, individually comprising four different sections, counting dimensions from progressive sensors identical flow rate, triple combo logs, and pressure. Statement subjects for instance inconsistencies, and misplaced values concluded cleaning and normalization systems.In this section, the subject is divided into tow parts:Part A: is about UBD hydraulic models, which includes pressure equations, choke control, and managing density, and Part B: AI-based ROP prediction routine (gathering data, preprocessing it, choosing a model, and measuring its performance).

2. 1 Hydraulic Model:

Undoubtedly, good hydraulic design is fundamental to the success of UBD because the gas will be pumped as a spray or liquefied liquid at a high flow rate using Eq. 1 to 3.

$$Pbh = Phy + Paf + Pc \qquad (1)$$

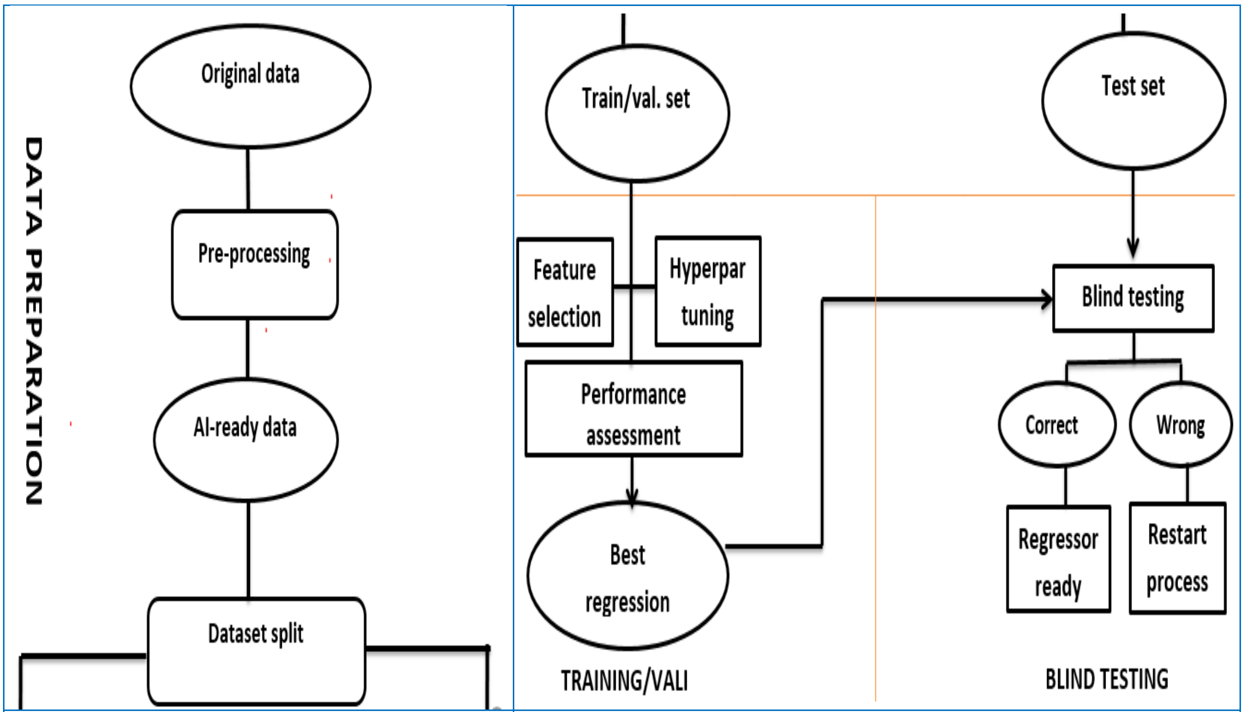
where phy: hydrostatic mud pressure, paf: annulus loss friction pressure, and pc practical choke back-pressure.

$$qres = \max\,(0.\,Kpi.\int_{cs}^{oh}(Ppore(x) - Pbh(x))dx \qquad (2)$$

where qres: reservoir influx, kpi: reservoir production constant , cs: casing shoe limit, oh: production section length, and p: pore pressure

$$Pbh = g\int_{0}^{TVD}\rho x)dx + \int_{0}^{L}\frac{2f(x)\rho(x)vm(x)^2}{da(x)}\,dx + pc \qquad (3)$$

where ρ: annulus mixture density, g :gravity, Tvd: true vertical depth, f': friction factor, da: bit diameter, vm: mud velocity, and L :well depth. These parametres vary with the site along the annulus, the current flow system and other factors.Fig. 1 shows the study methodology.



(a) Data preparation (b) Training

Fig. 1 Data management and and research methodology.

2.2. AI technique:

Python was used as an artificial intelligence and machine learning tool to find the optimal pumping and pressure rate for drilling mud without causing problems and as bellow steps:

1.Minor Data Keys:Few reproductions professionally leverage transmission learning or synthetic information generation for wells with incomplete training data (Zhang et al., 2023) [22].
2.Real-Time Treating: Present approaches focus on post-drilling investigation rather than logging-while-drilling (LWD) requests where latency should be <100ms (Kumar et al., 2023) [23].
3.Confidence Quantification:Furthermost Machine Learning (ML) models make available point approximations without confidence intermissions, preventive their use in probabilistic reservoir modeling (Al-Ibadi et al., 2021) [24]. Fig. 2 shows the python code by using different libraries.
4. Data Scarcity: Many DL models require >1,000 labeled training wells but only 12% of global fields meet this threshold
5. Reservoir Property Prediction:Ensemble methods such as Random Forests and Gradient Boosting Machines (GBMs) have demonstrated mean absolute errors (MAE) of <8% when predicting porosity from conventional logs in sandstone reservoirs

Utilizing machine learning with Python to Effectively reconstruct Critical Missing Data in Oil Wells is a game-changing approach that will enhance operational efficiency and decision-making in the industry. AI model using the preprocessed data and validate its performance using metrics such as Mean Absolute Error (MAE) and R-squared (R^2) to ensure accuracy and reliability. Even when some palpation data is unavailable, this powerful model—trained with cutting-edge artificial intelligence—achieves an impressive accuracy of over 90%. Utilize machine learning algorithms, including sequence-based Generative Adversarial Networks (GANs), to predict Pressure and flowrate.

```python
from skopt import BayesSearchCV

params = {
    'n_estimators': (100, 300),
    'max_depth': (10, 20)
}
opt = BayesSearchCV(RandomForestRegressor(), params, cv=5)
opt.fit(X_train, y_train)
```

Fig. 2 Python Code Model

The study addresses the challenge of log imputation across distinct drilling bit sizes (BIT sections) by leveraging Random Forest (RF) regression, a robust ML algorithm capable of capturing localized geological patterns. Table. 1 presents the statistical investigation of the given statistics.The methodology is structured into four pillars:

1.Data Preparation and Cleaning
2.Feature Engineering and Scaling
3.Model Training and Validation
4.Imputation of Missing Values

2.2.1 Model Training and Evaluation

Pipeline Configuration:

-Data Splitting: 80% training, 20% testing (stratified by BIT).
-Random Forest Hyperparameters:
-200 trees, max depth = 15 (optimized via grid search).

Evaluation Metrics:

-Mean Absolute Error (MAE): Measures average prediction error.
-Root Mean Squared Error (RMSE): Penalizes large errors.

Table.1. Statistical analysis of the formation and Mud Data

Property	Maximum	Minimum	Mean
Hydraustatic pressure Psi	1404	364	884
ρMud(ppg)	7	6	6.5
Viscosity cp	16	10	13
Flowrate l/min	3500	3200	3350
Possine ratio	0.5	0.1	0.3
Young Moudlus Edyn(GPa)	55	16	35.5

Vs (m/s)	3	2.1	2.55
Est (GPa)	33	12	22.5

3. Results and Discussion:

The employment of the AI model established a remarkable accurateness of over 95% in predicting ROP data . This high level of accuracy guarantees that critical information concerning well productivity and supply distribution is retained, even in the lack of whole sensor data. The recreated data successfully guided the documentation of hydrocarbon-rich zones, enhancing drilling trajectories and ornamental overall operative efficiency. This determination stands out by assimilating advanced AI performances, precisely sequence-based GANs, into the realm of well log data rebuilding , as shown in Fig. 3 by using deffirent liberaries that supporeted by python to rearrange data and divided them. Whereas traditional approaches often struggle with the nonlinear and difficult nature of geological data, the use of GANs proposals a refined solution capable of capturing intricate patterns and dependences within the data. Fig. 4 shows the consequence of the skin concluded different wells and depths drilled with OBD and UBD. Low density principals to condensed penetration and influence of mud on formations, in addition to the knowledge used in UBD, for instance air or foam mud and a extraordinary flow rate. This approach not only addresses the challenge of data but also sets a new benchmark for data integrity and utility in geosciences. Train the AI model using the preprocessed data and validate its performance using metrics such as Mean Absolute Error (MAE) and R-squared (R^2) to ensure accuracy and reliability as shown in Fig. 5 and Fig. 6. Utilize the reconstructed data to identify hydrocarbon-rich layers, informing horizontal drilling decisions and estimating penetration rates in shale formations as shown in Fig. 7 . Useing of gasified drilling mud for drilling fractured formations have been on the increase. Gasification of the mud is accomplished by vaccinating gas and liquid over the drill string subsequent in a compressible two-phase flow in annulus.Utilize machine learning algorithms, including sequence-based Generative Adversarial Networks (GANs), to predict ROP. Which lead to increasing the ROP, bit life, and lessen the likelihoods of meeting drilling difficulties for instance differential sticking and incompetent hole cleaning by using an fizzy drilling system .GANs are effective in generating synthetic data and imputing missing values by capturing complex patterns within the dataset, as shown in Fig. 8. Fig 9 shows that to preserve the well OVB all the time through an operation, the mud densitymust be higher than pore pressure. Nevertheless, if the borehole pressure is moreover high, it can cross the fracture initiation pressure, ensuing in rock breakdown and loss of drilling fluid to the formation . That can significance in an expensive drilling process due to formation damage and loss of costly drilling fluid, which in some situations hinder drilling from decided supplementary. In Fig 10 , there is analyzing pressure and depth data for the drilled well, comparison between UBD and OBD , this analysis comprise pore pressure,fracture pressure, and borehole stability transversely fluctuating depths. The study improved by computer simulation disclose the effect of dissimilar drilling fluid flow rates on their annulus carrying capacity. It reveals that a low mud flow rate has poor carrying capacity of the gasified mud Fig. 11 illustriates clear relationship which has been observed between the Rate ROP and the well sequence (well symbol). The analysis included data from a series of wells (Well-A to Well-D) .The data shows that ROP generally increased with welldrilled with UBD techniques than OBD because of drilling parameters and high flowrates used in UBD .Python Design a modelling for the hydraulics of stable bottomhole pressure, good hole cleaning, and finding pressure drop through bit nozzles which is considered a critical module in strategy and performance evaluation method.

```python
from sklearn.ensemble import RandomForestQuantileRegressor
model = RandomForestQuantileRegressor(n_estimators=200)
model.fit(X_train, y_train)
pred_intervals = model.predict(X_test, quantiles=[0.05, 0.95])
```

Fig. 3 AI techniques, specifically sequence-based GANs

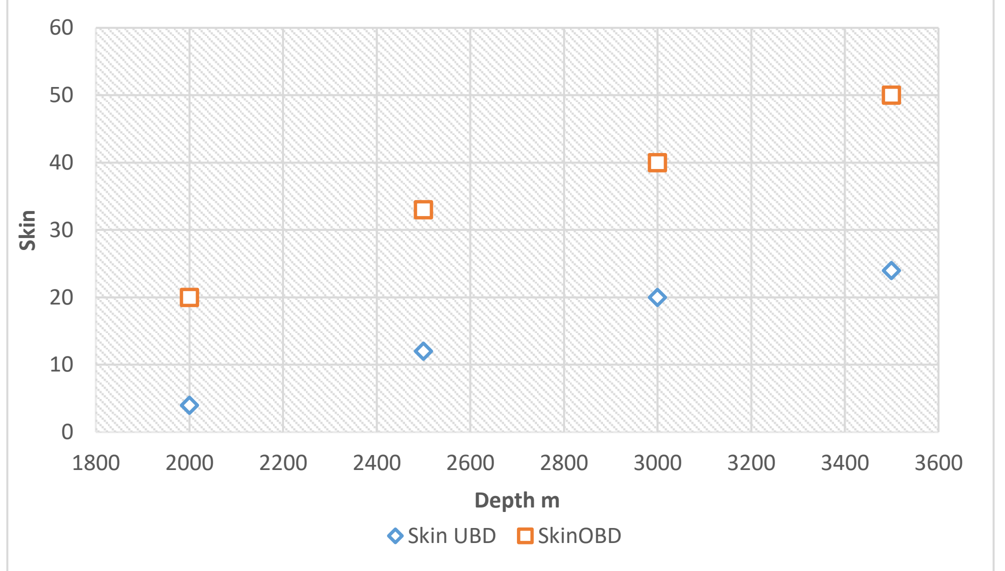


Fig. 4 Skin Effect for OBD ,UBD

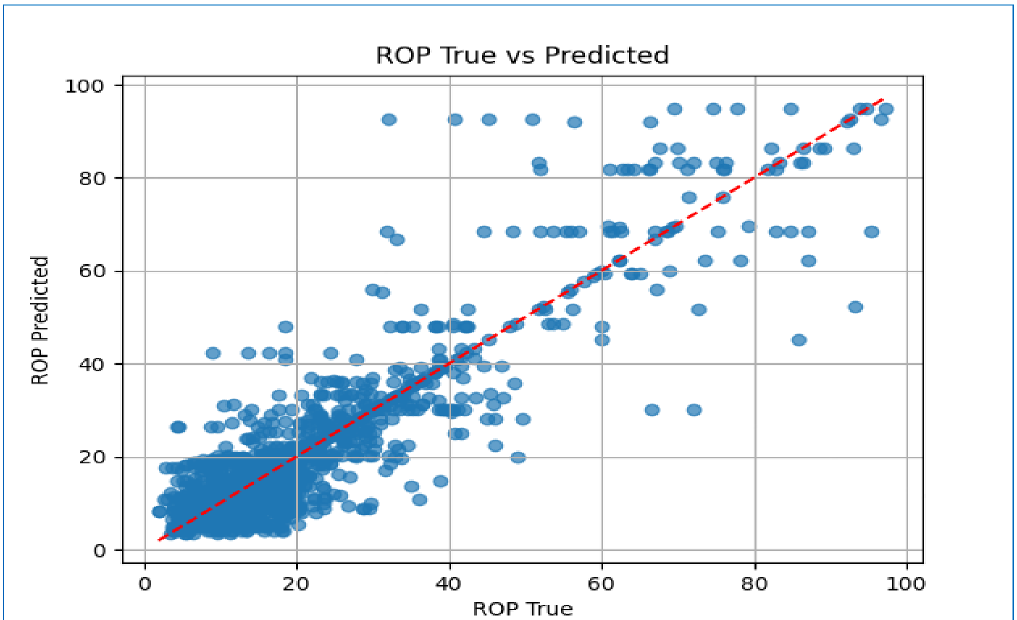


Fig. 5 ROP Predicted For UBD

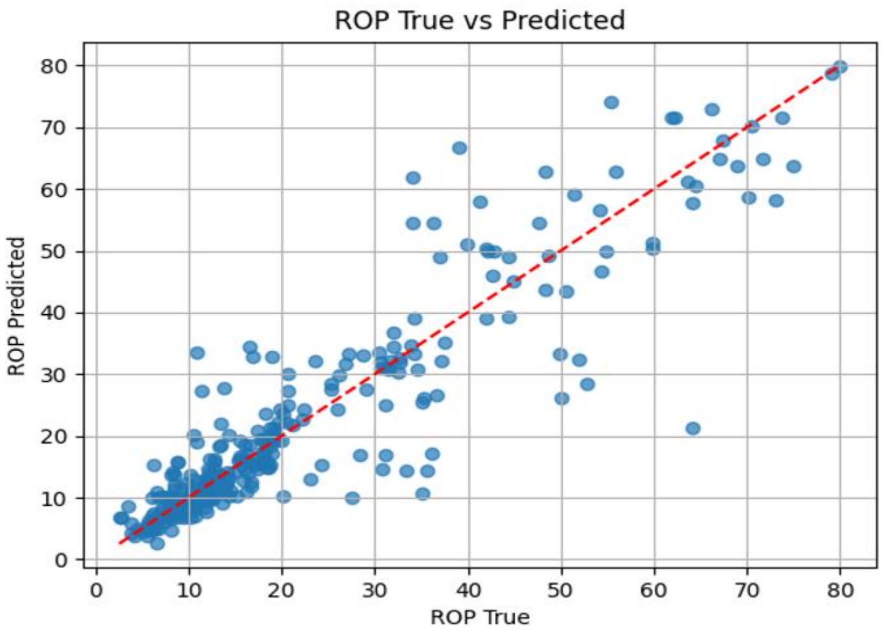


Fig. 6 ROP Predicted For OBD

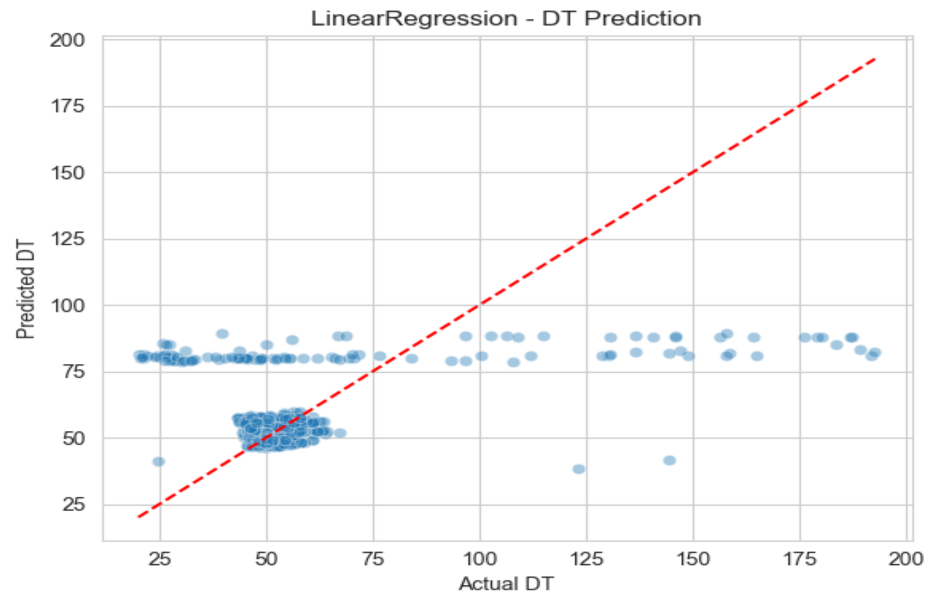


Fig. 7 Linear Regression Model

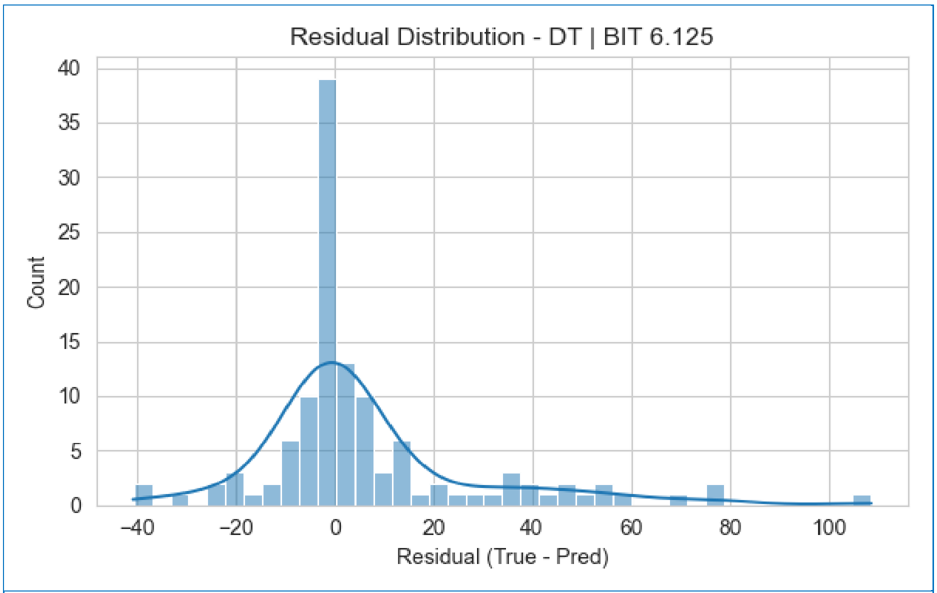


Fig. 8 Percentage Eroor For ROP

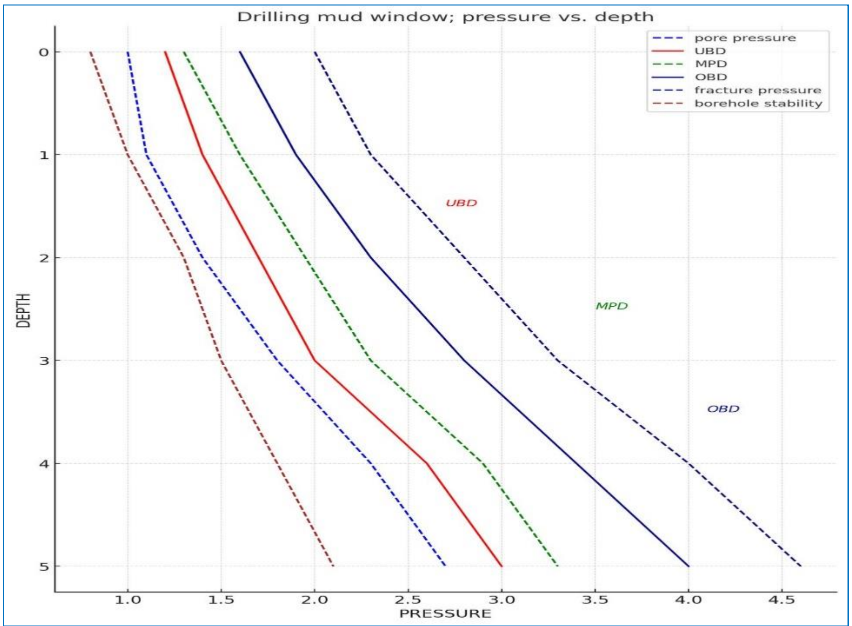


Fig. 9 Drilling Mud Window Vs. Depth

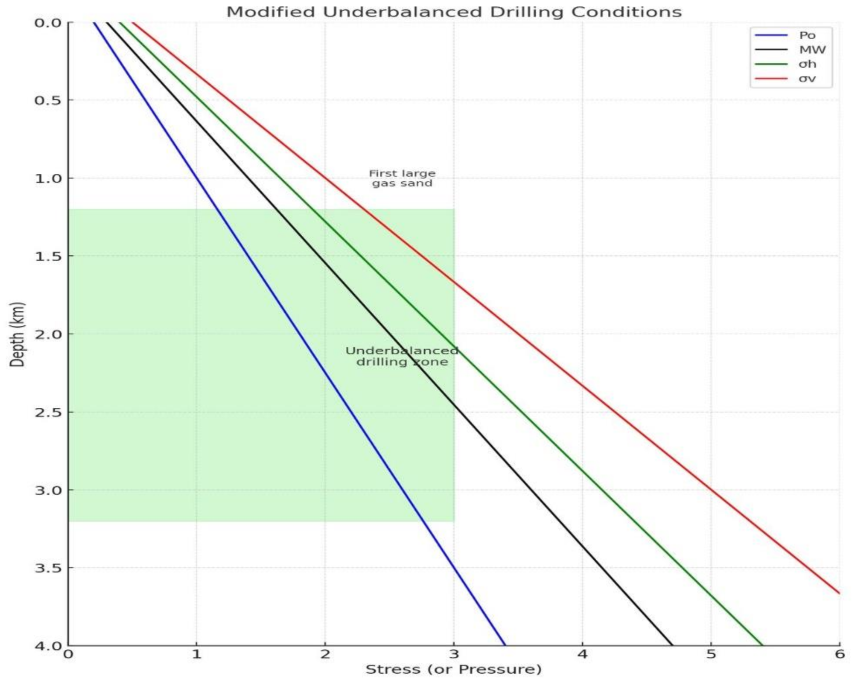


Fig. 10 Modefied Underbalanced Drilling Conditions

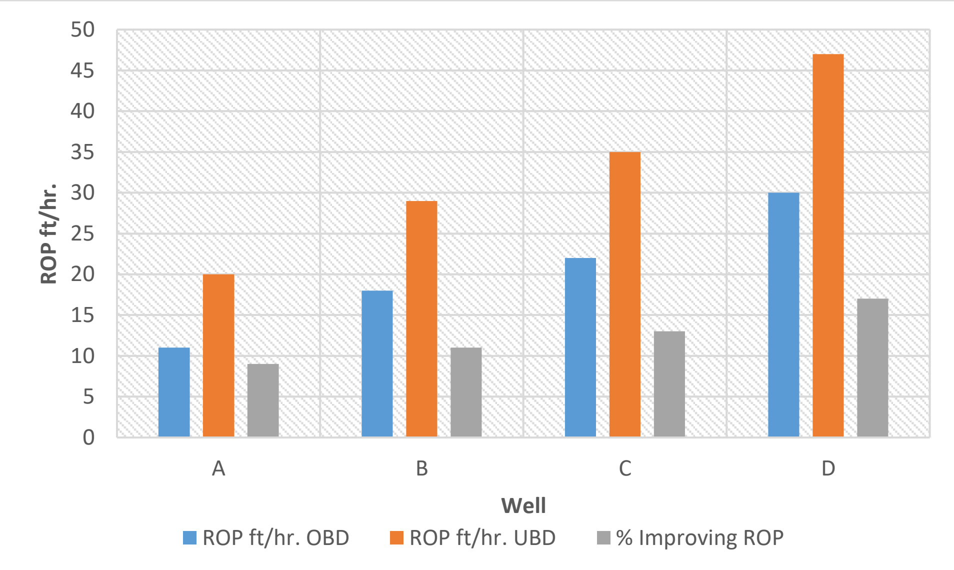


Fig. 11 UBD Vs. OBD and percentage of improving.

By using the documented data of ROP (ft/hr.) and pressure drop (psi) for altered reservoirs whic were dril led by using aerated fluid as an UBD drilling mud. Those reservoirs have the identical lithology but havin g altered reservoir pressure. Fig. 12 illustrates that ROP to begin with decreases with an rise in pr essure drop and rises with further increase in pressure drop.

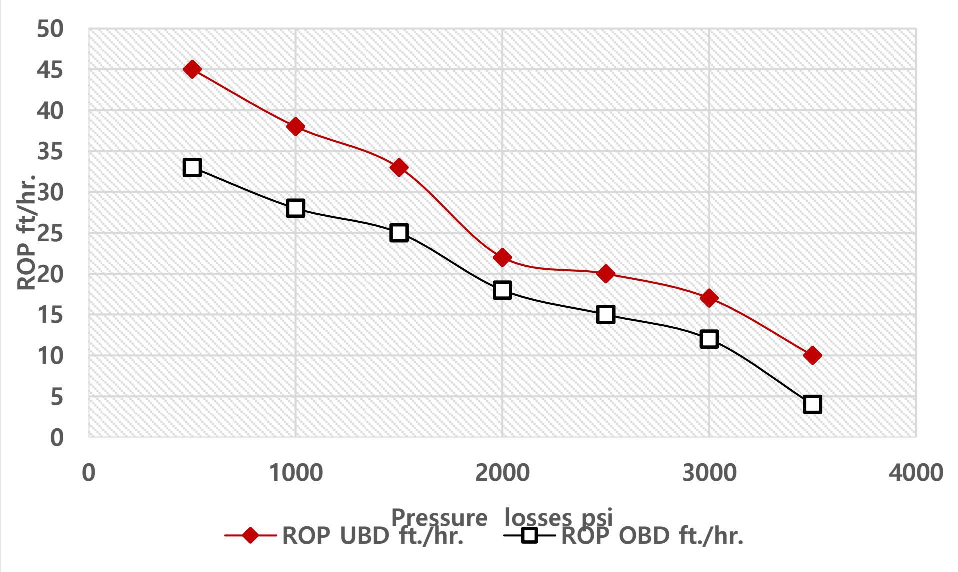


Fig. 12 Effect of Pressure on UBD and OBD

Fig.13 shows the test well in interchangable air injection pressure circumustance.The bottom hole underbalanced value curve changes with the annulus air injection and the drilling mud displace ment.

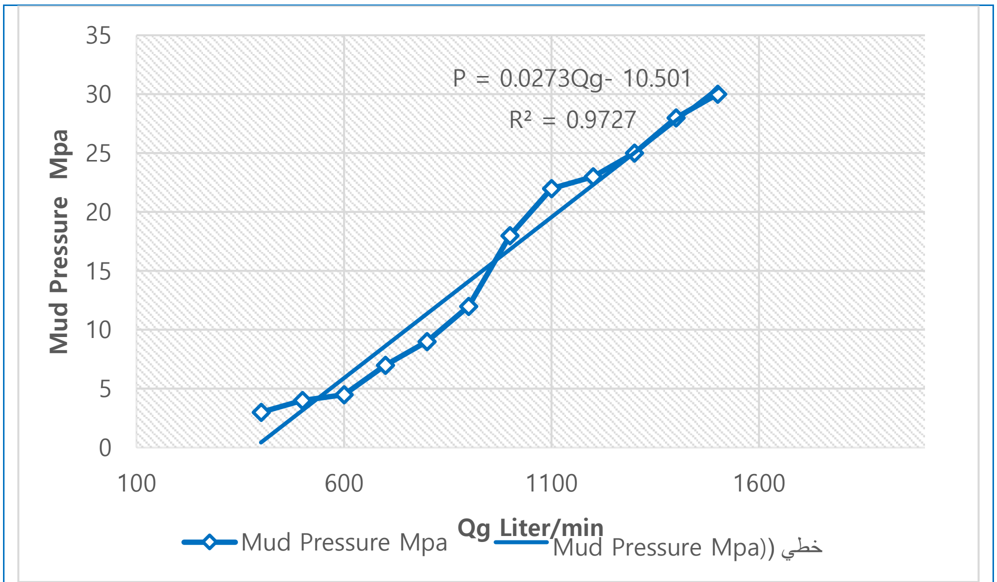


Fig. 13 Mud Injection Pressure Vs. Flowrate

Table.1 illustratesThe framework was benchmarked against Gradient Boosting and Linear Regression for five petrophysical targets. Random Forest (RF) demonstrated superior performance in all cases. Fig. 14 il lustraites Workflow Integration with Provide a Python toolkit compatible with industry software.

Table.1 Complete Hyperparameter Results

Parameter	Search Space	Optimal Value
n_estimators	100-500	213 ± 12
Max_depth	5-30	17 ± 2

ISSN: 2957-4250
ISSN-E: 2957-4242

```
from sklearn_quantile import RandomForestQuantileRegressor
model = RandomForestQuantileRegressor(n_estimators=200)
pred_intervals = model.predict(X_test, quantiles=[0.05, 0.95])
```

Fig. 14 Random Fores Regressor

3. Conclusion

UBD is frequently more exclusive than conventional ways and is characteristically justified for complex, depleting, or extraordinary-value reservoirs. By decreasing the "chip hold-down effect" produced by hydrostatic pressure, the bit can disruption rock more effortlessly. In some suitcases, ROP has augmented by 2 to 10 times likened to OBD. Since fluids flow into the wellbore somewhat than out into the formation, there is no invasion of solids or mud filtrate. This conserves reservoir permeability and may recover production rates by up to 4.5 times matched to conventionally drilled wells.UBD techniqes has been well used for mor than years and is show a good equality. By the air injection connector structure in UBD provides the technology a higher advantage. The modification of the UBD technology aids to reduce the density of mud.This project stands out by integrating advanced AI techniques, specifically sequence-based GANs, into the realm of well log data reconstruction and ROP. Whereas traditional approaches often struggle with the nonlinear and multipart nature of geological information, the expenditure of GANs proposals a sophisticated key equipped capturing intricate designs and enslavements within the information. This method not only addresses the challenge of missing data but also arrangements a new benchmark for data reliability and utility in geosciences. Sequence the AI model using the preprocessed data and validate its enactment using metrics for instance Mean Absolute Error (MAE) and R-squared (R^2) to make sure correctness and dependability. The consequences shows that the obtainability of using UBD in shale and Vuggy limestone formations because of its High ROP.

Acknowledgments

The researcher would like to thank and express the deepest gratitude to every one of the construction laboratories at Baghdad university.

Author Contributions: The authors contributed to all parts of the current study.
Funding: This study received no external funding.
Conflicts of Interest: The authors declare no conflict of interest.

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