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Deep Learning-Based Prediction of Bottomhole Pressure Variations During Underbalanced Drilling Operations

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Abstract

Underbalanced drilling (UBD) offers significant advantages over conventional drilling operations by minimizing formation damage and enhancing drilling efficiency. However, fluctuations in bottomhole pressure (BHP) during UBD operations can temporarily create overbalance conditions, potentially damaging the reservoir and reducing productivity. Accurate prediction and control of BHP are therefore critical to the success of UBD operations. The present paper investigates the application of deep learning approaches, specifically Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks, for predicting BHP variations. A comprehensive dataset from the published literature was employed to train the models. Statistical indices, including Mean Absolute Percentage Error (MAPE) and root mean square error (RMSE), were used to evaluate the models' performance. The results indicate that both LSTM and GRU models show significant promise in predicting BHP, with the GRU model slightly outperforming the LSTM. The finding of this study can assist the industry in enhancing UBD safety, efficiency, and formation protection by enabling more accurate prediction and control of B.

Keywords: *Underbalanced Drilling; Bottomhole Pressure; Deep Learning; LSTM; GRU.*

1. Introduction

Underbalanced drilling (UBD) is a technique used to enhance drilling efficiency and minimize formation damage by maintaining bottomhole pressure (BHP) below formation pressure [1]. This method aims to reduce the invasion of drilling fluids into the formation, thereby improving well productivity. However, accurately predicting BHP during UBD operations is challenging due to the complex and dynamic nature of the drilling environment [2]. Traditional prediction methods often rely on physical models that require extensive calibration and may not fully capture the nonlinear interactions between various drilling parameters. Moreover, maintaining the desired underbalance state can be particularly difficult during drilling interruptions or connections, leading to fluctuations in BHP and potentially resulting in temporary overbalance scenarios [3].

This limitation paves the way for the application of data analytics and data-driven models. Machine learning (ML) has revolutionized various aspects of the oil and gas industry by enabling the prediction of critical parameters [4–9]. Previous studies [10–13] revealed that ML algorithms can analyse vast datasets of field data to identify patterns and predict reservoir properties, thereby optimizing well placement and production strategies [14]. Additionally, Ferreira *et al.* [15] investigated the application of ML models for predicting equipment failures and proactively scheduling maintenance procedures. This approach helps minimize downtime and optimize maintenance costs [16]. Other studies conducted by [17–20] have employed data-driven models to analyse real-time drilling data and optimize drilling parameters, such as the rate of penetration (ROP), to reduce drilling costs.

Early research focused on employing ML algorithms to predict bottomhole pressure (BHP) under steady-state conditions. Pioneering studies by Osman *et al.* [21] and Jahanandish *et al.* [22] established the foundation by demonstrating the effectiveness of artificial neural networks (ANNs) in predicting BHP for vertical wells with multiphase flow. Osman *et al.* [21] compared an ANN model with existing correlations, achieving lower errors. Jahanandish *et al.* [22] built upon this by validating the approach across different network architectures and datasets. The exploration of machine learning for BHP prediction extended beyond ANNs. Feili Monfared *et al.* [23] investigated the use of fuzzy inference systems (FIS) for BHP prediction in unconventional reservoirs. Ashena and Moghadasi [24] applied ANNs to predict pressure drop in the annulus, introducing various optimization algorithms like Genetic Algorithms (GA) and Ant Colony Optimization (ACO) to improve model performance. Nasimi *et al.* [25] further explored optimization techniques for ANNs. They compared Particle Swarm Optimization (PSO) and a combination of ACO with Backpropagation (BP) to achieve faster and more accurate BHP predictions in UBD. In studies conducted by Sami and Ibrahim [26] and Zolfagharroshan and Khamehchi [27], the performance of ANNs was compared with other machine learning models such as Random Forest (RF), K-Nearest Neighbors (KNN), Radial Basis Function (RBF) neural networks, Least-Squares Support Vector Machines (LSS VMs), and Genetic Programming (GP) for BHP prediction during production. Ashena *et al.* [28] extended the application of ANNs to predict BHP in inclined wells, demonstrating the potential for broader wellbore configurations. Okoro *et al.* [29] employed Extremely Randomized Tree and Feed Forward Neural Network (FFNN) models for BHP prediction in UBD. Notably, Spesivtsev *et al.* [30] made a significant leap forward by employing ANNs to predict BHP in transient multiphase flows, effectively handling interdependent time series data. Building on previous studies, it is evident that the field of machine learning for BHP prediction has evolved considerably. While early research focused on steady-state conditions, recent advancements, like those by Spesivtsev *et al.* [30], have enabled high-accuracy BHP predictions in time-dependent scenarios. This capability enhances wellbore optimization, leading to improved production efficiency and reservoir management.

Recent advances in machine learning (ML) have introduced new opportunities for predictive analytics in the oil and gas industry. Techniques such as GRU networks and LSTM networks have shown promise in modelling the complex, nonlinear relationships inherent in drilling data. These approaches excel at handling sequential data and can effectively learn from historical drilling information. The present paper aims to implement GRU and LSTM networks to improve the accuracy of predicting BHP during UBD operations. It represents a significant advancement in the field, as, to the best of our knowledge, it is the first to apply GRU and LSTM networks for predicting BHP changes during underbalanced drilling (UBD) operations. Unlike previous approaches, which primarily relied on traditional machine learning models or focused on steady-state conditions, this study leverages the strengths of deep learning techniques to capture the intricate and time-dependent nature of BHP variations. By analysing historical data to identify trends, GRU and LSTM networks can capture the intricate relationships between variables like nitrogen injection rate, oil injection rate, and wellhead pressure. This capability allows them to predict BHP fluctuations with high accuracy, even during transient states like connections. By utilizing historical data to identify patterns and trends that traditional methods might overlook, these models offer improved accuracy in predicting BHP during UBD operations.

2. Theorical background

2.1. Underbalanced drilling

Underbalanced drilling is a drilling technique in which the pressure in the well is maintained lower than the formation pressure. This approach offers several advantages over conventional drilling methods. By maintaining a lower pressure in the wellbore than in the formation, UBD minimizes the penetration of drilling fluids into the formation. This reduces the risk of formation damage, which can significantly reduce well productivity. Additionally, UBD facilitates hydrocarbon recovery during the drilling process. This can lead to increased well productivity and potentially shorter payback periods. The lower pressure environment in UBD promotes better well cleaning by facilitating the removal of cuttings and debris. This improves drilling efficiency and reduces the risk of stuck pipe incidents [31]. Building on these advantages, UBD offers potential benefits for wellbore productivity. However, its implementation requires meticulous planning and execution to avoid exceeding formation pressure and inducing wellbore damage. Compared to well-designed conventional overbalanced drilling programs, poorly designed and/or executed UBD programs can lead to more severe formation impairment.

Several key challenges are inherent to UBD operations. Firstly, maintaining a consistently underbalanced condition throughout the drilling process presents significant difficulties. Pressure fluctuations can occur during routine operations, such as drill pipe connection procedures, where the temporary cessation of nitrogen injection leads to a transient increase in bottom hole pressure (BHP). These overbalanced situations can negate the advantages of UBD and potentially inflict more formation damage due to fluid invasion. Secondly, UBD programs are often associated with increased costs and safety concerns. The specialized equipment and procedures required for UBD operations necessitate a higher capital expenditure compared to conventional drilling. Additionally, the influx of formation fluids during UBD introduces the risk of uncontrolled hydrocarbon flow, posing a potential safety hazard.

In conclusion, while UBD offers potential benefits, its implementation requires careful consideration of the associated challenges. Maintaining precise pressure control throughout the drilling process is crucial to avoid exceeding formation pressure and inducing wellbore damage. Furthermore, the increased cost and safety concerns necessitate a thorough evaluation of the project's feasibility before embarking on a UBD program [32].

2.2. Recurrent neural networks (RNNs) for time-series prediction

RNNs are a class of artificial neural networks specifically designed to process sequential data. Traditional neural networks struggle with sequential data because they treat each data point independently. RNNs overcome this limitation by incorporating internal memory mechanisms that allow them to learn from past data points and use this information to make predictions for future points. This ability makes RNNs well suited to tasks such as time series prediction, where the future value depends on the historical sequence of data points [33].

Two specific types of RNNs that have gained significant popularity for time series prediction tasks are LSTM) and GRU networks. LSTMs address a significant limitation of standard RNNs, known as the vanishing gradient problem. This problem arises when processing long sequences of data, where the influence of earlier data points can fade as the network propagates information forward. LSTMs contain a gated memory cell that allows them to selectively store and access information over long periods of time, enabling them to capture long-term dependencies within sequential data. In the other hand, GRUs offer a simpler alternative to LSTMs while achieving comparable performance in many tasks. They use a gate mechanism similar to LSTMs, but with a slightly less complex architecture. This simpler structure can make GRUs more computationally efficient than LSTMs, while still effectively capturing temporal dependencies in sequential data [34].

3. Data description and pre-processing

The current study investigates two distinct machine learning models for predicting BHP changes in UBD, namely, GRU, and LSTM. By training the models on data from wells with similar geological formations, and using drilling rigs with comparable specifications, we can tailor the models to capture the specific pressure response patterns relevant to the UBD operation in question. This customization has the potential to provide more accurate BHP predictions than generic software solutions applied to different well conditions. To do this end, a comprehensive dataset was collected to train the ML models. This dataset was extracted from readily available graphs of three horizontal wells. These wells, drilled in Algerian oilfields using

UBD, target oil from Cambrian formations through horizontal sections. The dataset captures key parameters crucial for predicting bottom hole pressure (BHP) change, including time, BHP, nitrogen injection flow rate (q_{N_2}), oil flow injection rate (q_o), and wellhead pressure (WHP). BHP is the primary target variable that the models aim to predict, with measurements taken at regular intervals throughout the UBD well operations. The time data provides the temporal context necessary for the models to capture the sequential nature of BHP variations.

Tables 1-3 summarize the dataset for Wells 1, 2, and 3, respectively. The statistics include the count, mean, standard deviation, minimum, 25th percentile, median, 75th percentile, and maximum values. This comprehensive view allows for a better understanding of the range and variability of the data used in the predictive modelling.

Table 1. Descriptive statistics of input and output parameters for well 1.

	BHP (psi)	N_2 rate (L/min)	Oil rate (Lmin)	WHP (psi)
Count	955	955	955	955
Mean	2595.26	28.34	566.17	189.64
SD	78.05	9.31	206.88	93.25
Min	2473.98	0	0	2.41
25%	2549.34	30.81	587.75	133.38
50%	2570.6	31.29	664.65	158.59
75%	2630.51	32.28	670	202.34
Max	2941.63	34.24	706.01	536.83

Table 2. Descriptive statistics of input and output parameters for well 2.

	BHP (psi)	N_2 rate (L/min)	Oil rate (Lmin)	WHP (psi)
Count	649	649	649	649
Mean	2756.36	21.12	506.76	160.92
SD	59.99	11.63	266.53	65.18
Min	2644.45	0	0	41.05
25%	2712.36	26.67	546.16	106.13
50%	2743.6	27.3	650.21	136.61
75%	2804.72	27.72	655.13	219.06
Max	2916.1	28.98	725.65	335.03

Table 3. Descriptive statistics of input and output parameters for well 3.

	BHP (psi)	N_2 rate (L/min)	Oil rate (Lmin)	WHP (psi)
Count	720	720	720	720
Mean	2972.28	26.1	513.9	142.24
SD	64.94	12.61	248.1	74.98
Min	2761.76	0	0	47.24
25%	2929.57	30.78	536.8	80.05
50%	2964.12	32.2	636.05	111.52
75%	3011.15	32.55	650.77	216.1
Max	3174.22	36.75	708.98	316.59

Before the data can be used to train machine learning models, several pre-processing steps are essential to ensure data quality and model effectiveness. The data was carefully examined to identify and remove inconsistencies, errors, or missing values. Extreme data points, known as outliers, which are significantly different from the rest of the data, can distort the model's learning process. These outliers were identified and removed prior to modelling to ensure the data more accurately reflects underlying trends and patterns. Missing data points were addressed using interpolation techniques, which estimate missing values based on surrounding data. This approach helps to minimize the impact of missing data on model training. Subsequently, BHP values along with the input parameters were normalized to a common scale using the MinMaxScaler approach, which scales the data between 0 and 1. This normalization ensures that all features contribute equally to the training process and prevents features with larger scales from dominating the model's learning.

Another pre-processing steps involved accounting for the time it takes for WHP to affect BHP. To address this, we lagged the WHP data by creating a new feature that reflects the WHP value from a previous time step. Incorporating lagged data allows the model to learn the temporal relationship between WHP and BHP. Since WHP has a significant impact on BHP, we applied a scaling factor to the WHP data to emphasize its importance. This scaling factor increases the weight of WHP relative to other features during normalization. This emphasizes the importance of WHP in the learning process of the model and improves the model's ability to capture the nuances of this relationship. Finally, the UBD data was divided into two sets: a training set and a testing set. 50% of the data was allocated to the training set, used to train the models, and the other 50% was employed as a testing set to evaluate the model's generalizability on unseen data.

4. Results and discussion

4.1. Model development

As previously mentioned, the current study investigates two distinct machine learning models for predicting BHP changes in UBD operations: GRU, and LSTM. Both models were trained and evaluated using the same data described above, allowing for a fair comparison of their performance in predicting BHP. To achieve optimal performance from the LSTM and GRU models, we employed a hyperparameter tuning process. This process involves systematically evaluating different combinations of hyperparameter values and selecting the configuration that yields the best results on a validation set. The mean squared error (MSE) loss function was employed to measure the difference between the predicted BHP values and the actual BHP values. The models were trained to minimize this loss function, leading the model to learn patterns in data that can accurately predict future BHP changes.

Table 4 summarizes the hyperparameters for both LSTM and GRU models. The GRU model architecture consists of a GRU layer with 64 units. It is followed by three dense layers, each with 128 units and ReLU activation function. The optimizer used is Adam with a learning rate of 0.01. This model aims to predict BHP changes by processing sequences of data from UBD operations, with specific considerations for WHP scaling factor and a lag time of 9. The LSTM model utilizes the best hyperparameters identified through tuning. It includes an LSTM layer with 64 units for sequence processing. The subsequent architecture comprises two dense layers, each with 64 units and ReLU activation. The model is optimized using Adam with a learning rate of 0.01. This configuration is designed to effectively capture the temporal dependencies in the data related to BHP changes during UBD operations, leveraging insights from the lag time of 9 and WHP scaling factor of 5.

Table 4. Hyperparameter settings for the GRU and LSTM networks.

Hyperparameter	Options
GRU units	32, 64, 128, 256
LSTM units	32, 64, 128, 256
Dense layers	1, 2, 3
Dense units	32, 64, 128, 256
Learning rates	0.01, 0.001
WHP scaling factors	1, 3, 5, 7, 9, 11
Lag time	9, 13, 17

4.2. Model assessment

Once trained, the models were evaluated on the testing set in order to assess their relative effectiveness in predicting BHP changes during UBD operations. The models predict BHP values for the testing data points, and these predictions were compared to the actual BHP measurements. Two metrics, namely, mean absolute percentage Error (MAPE) and root mean square error (RMSE), were employed to quantify the accuracy of the predictions. A lower MAPE and RMSE values indicates better model performance, signifying that the model's predictions are closer to the actual values. The mathematical expression of these statistical metrics are given by:

$$\text{MAPE} = \frac{1}{N}\sum_{i=1}^{N}\frac{(|y_i - x_i|)}{y_i} \times 100 \qquad (1)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - y_i)^2} \qquad (2)$$

where: y_i is the actual value of measured BHP, x_i denotes the predicted value of BHP, and N refers to the total number of data points.

Table 5 reports the results for each model after evaluation in wells 1, 2, and 3, respectively, based on the testing subset. As it can be seen in this table, the GRU model consistently shows better performance compared to the LSTM model across all wells. Specifically, it achieves lower RMSE values of 49.051, 53.272, and 45.703 for Wells 1, 2, and 3, respectively, compared to LSTM's RMSE values of 50.772, 55.640, and 49.968. The GRU model also records lower MAPE values of 1.30%, 1.59%, and 1.25% for the same wells, while LSTM's MAPE values are 1.34%, 1.73%, and 1.32%. These results indicate that the GRU model provides more accurate predictions with fewer errors across all wells, suggesting it is better suited for capturing BHP variations during UBD operations.

Table 5. Performance metrics for GRU and LSTM models in BHP prediction using the testing subset.

	Well 1		Well 2		Well 3	
	LSTM	GRU	LSTM	GRU	LSTM	GRU
MAPE (%)	1.34	1.30	1.73	1.59	1.32	1.25
RMSE	50.772	49.051	55.640	53.272	49.968	45.703

The performance of the established GRU models for predicting bottom hole pressure (BHP) in wells 1, 2, and 3 was further assessed through graphical analysis. Figs. 1-3 compare the predicted BHP from GRU model to the actual measured BHP for each well. These figures also include inputs parameters, namely, nitrogen injection flow rate, oil injection flow rate, and wellhead pressure, which influence the BHP within the well. As observed, the predicted BHP (orange line) closely matches the actual BHP (green line) in both the training and testing phases, indicating strong model accuracy and generalization. Furthermore, the developed GRU model was able to follow the trend of the measured BHP with respect to the input parameters. The model's ability to align predictions with actual outcomes demonstrates its effectiveness and the relevance of the selected inputs.

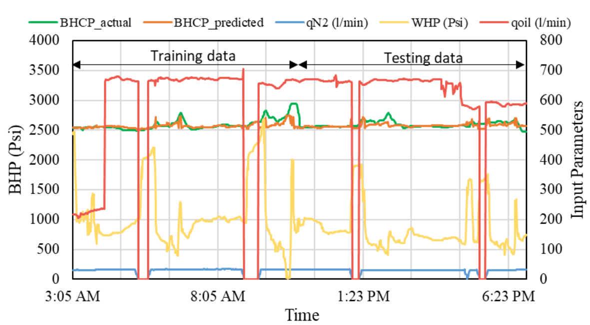

Fig. 1. GRU model prediction of BHP vs. measured BHP under: nitrogen injection, oil injection, and wellhead pressure in well 1.

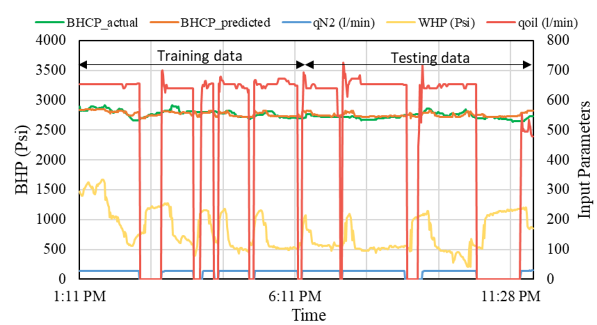

Fig. 2. GRU model prediction of BHP vs. measured BHP under: nitrogen injection, oil injection, and wellhead pressure in well 2.

Fig. 4 depicts the relative deviation of the BHP values predicted by GRU model against the actual BHP for wells 1, 2, and 3, with subfigures (a), (b), and (c) corresponding to each well respectively. According to these plots, the relative deviation generally remains within ±10% across all three wells. Most data points are clustered around the zero-deviation line, indicating that the model generally predicts BHP with good accuracy. Fig. 5 presents a cumulative distribution function (CDF) of the MAPE for the GRU model in the three wells. This plot reveals

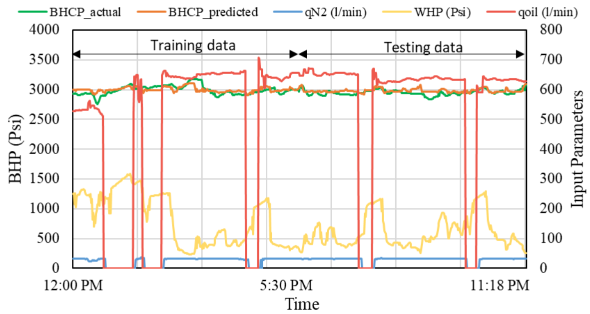

Fig. 3. GRU model prediction of BHP vs. measured BHP under: nitrogen injection, oil injection, and wellhead pressure in well 3.

that over 95% of the predictions made by the GRU model have a MAPE below 6% in the three wells. The overall analysis suggests that the GRU model is highly effective in predicting BHP, with most predictions on unseen data being highly accurate, demonstrating the strong generalization capability of the GRU model.

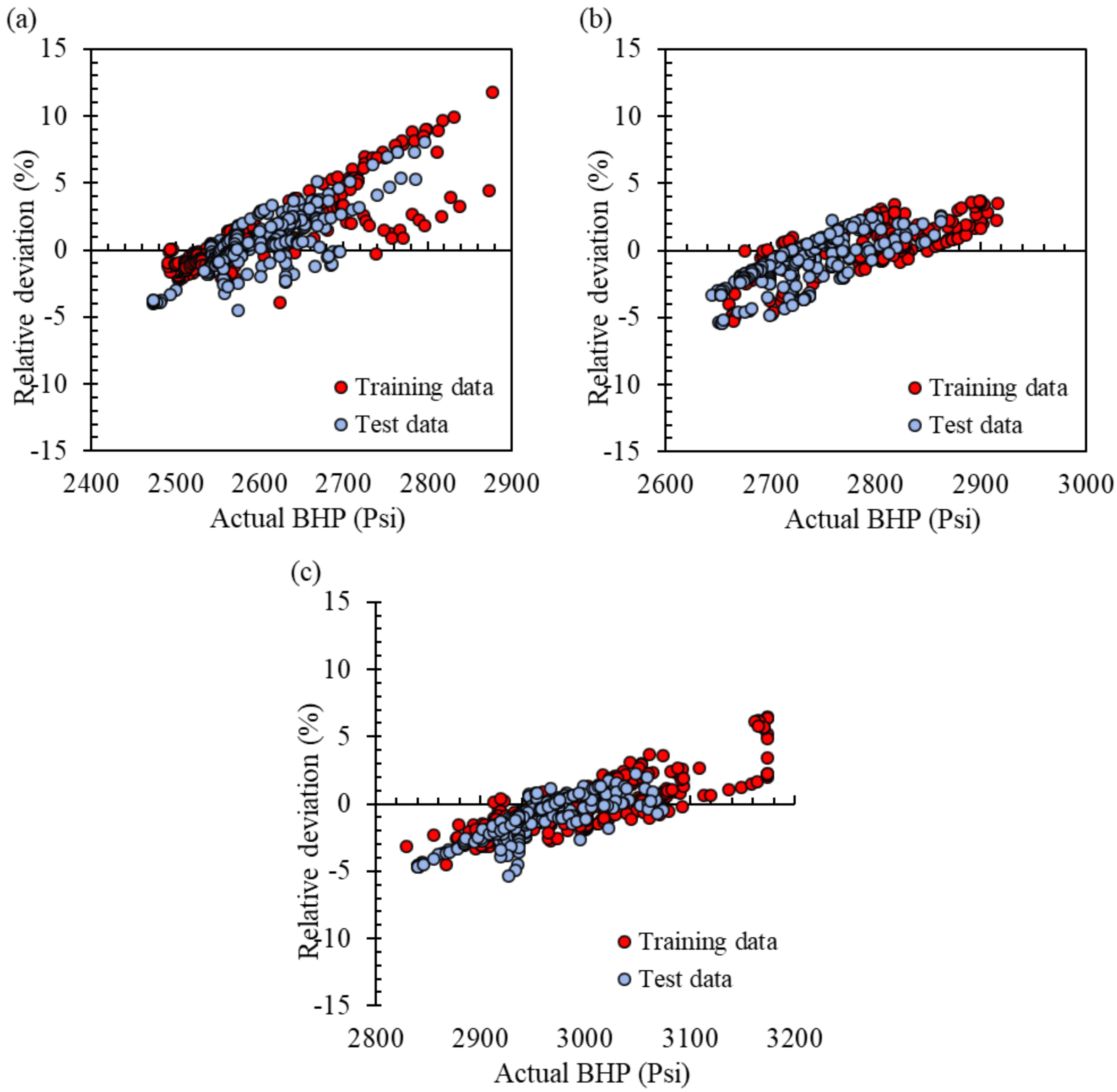

Fig. 4. Relative deviation of the BHP values predicted by the GRU model against the actual BHP for Wells 1, 2, and 3. Subfigures (a), (b), and (c) correspond to Wells 1, 2, and 3, respectively.

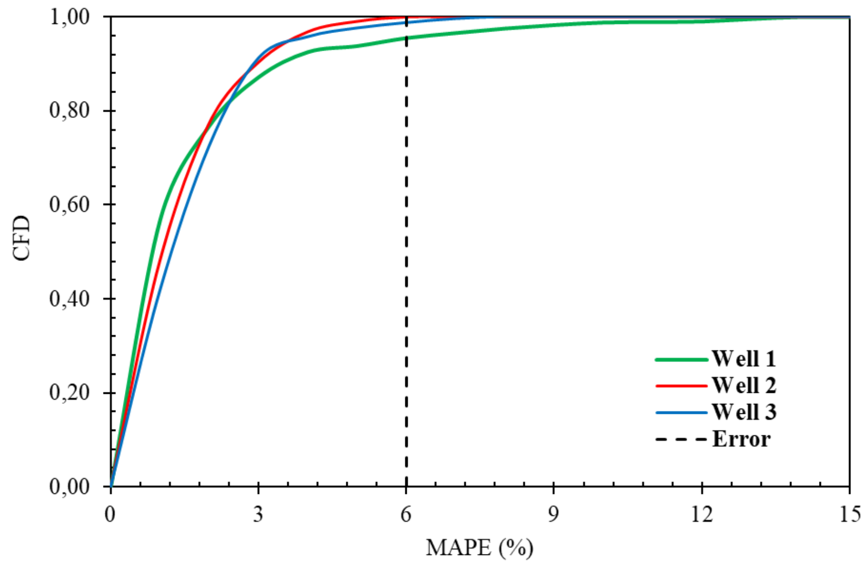

Fig. 5. Cumulative distribution function (CDF) of the mean absolute percentage error for the GRU model predictions in Wells 1, 2, and 3.

Modeling often requires simultaneously defining the model's applicability domain and assessing its validity. Various techniques are available for identifying outlier data, with the Leverage approach being noted for its precision. A detailed explanation of the Leverage approach can be found in the following paper [35]. Fig. 6 presents the Williams plot for the GRU model's outcomes across the three wells. As observed, it is clear that most data points fall within the range $-3 \leq R \leq 3$ and $0 \leq H \leq H*$, where H* represents the warning Leverage value. The fact that the majority of data is within the $0 < H < H*$ and $-3 < R < 3$ range indicates that the results lie within the applicability domain, which validates the model. 'Good High Leverage' points, which are data within the $H* \leq H$ and $-3 \leq R < 3$ range, are not within the applicability domain but are predicted accurately. However, other data within this domain might not be predicted accurately. Additionally, 'Bad High Leverage' points, located in the $R > 3$ or $R < -3$ range, are experimentally flagged as suspect data. In this study, 39 data points from the three wells were identified as being outside the applicability domain, representing 1.80% of the total data points, and were recognized as experimentally suspect data. Moreover, 60 data points from the three wells, which represent 2.77% of the total data points, were identified as 'Good High Leverage' points. These results indicate that the proposed GRU model is capable of accurately predicting BHP across a wide range of input parameters.

4.3. Importance of the machine learning for BHP prediction

By accurately predicting BHP variation, machine learning models can assist drilling engineers in proactively adjusting drilling parameters to maintain the desired underbalance state. This can help to minimize the risk of overbalance situations and maximize the benefits of UBD. Machine learning models have the potential to be integrated into real-time drilling monitoring systems. This would allow for continuous prediction of BHP changes and enable engineers to make data-driven adjustments to drilling parameters as needed, optimizing the overall UBD process. While commercial software offers advantages like domain expertise and user-friendliness, machine learning models possess distinct strengths.

Their data-driven nature allows them to potentially adapt to new situations and improve accuracy over time as more data becomes available. Additionally, machine learning models can be customized to specific well conditions by training them on relevant historical data from similar wells or rigs.

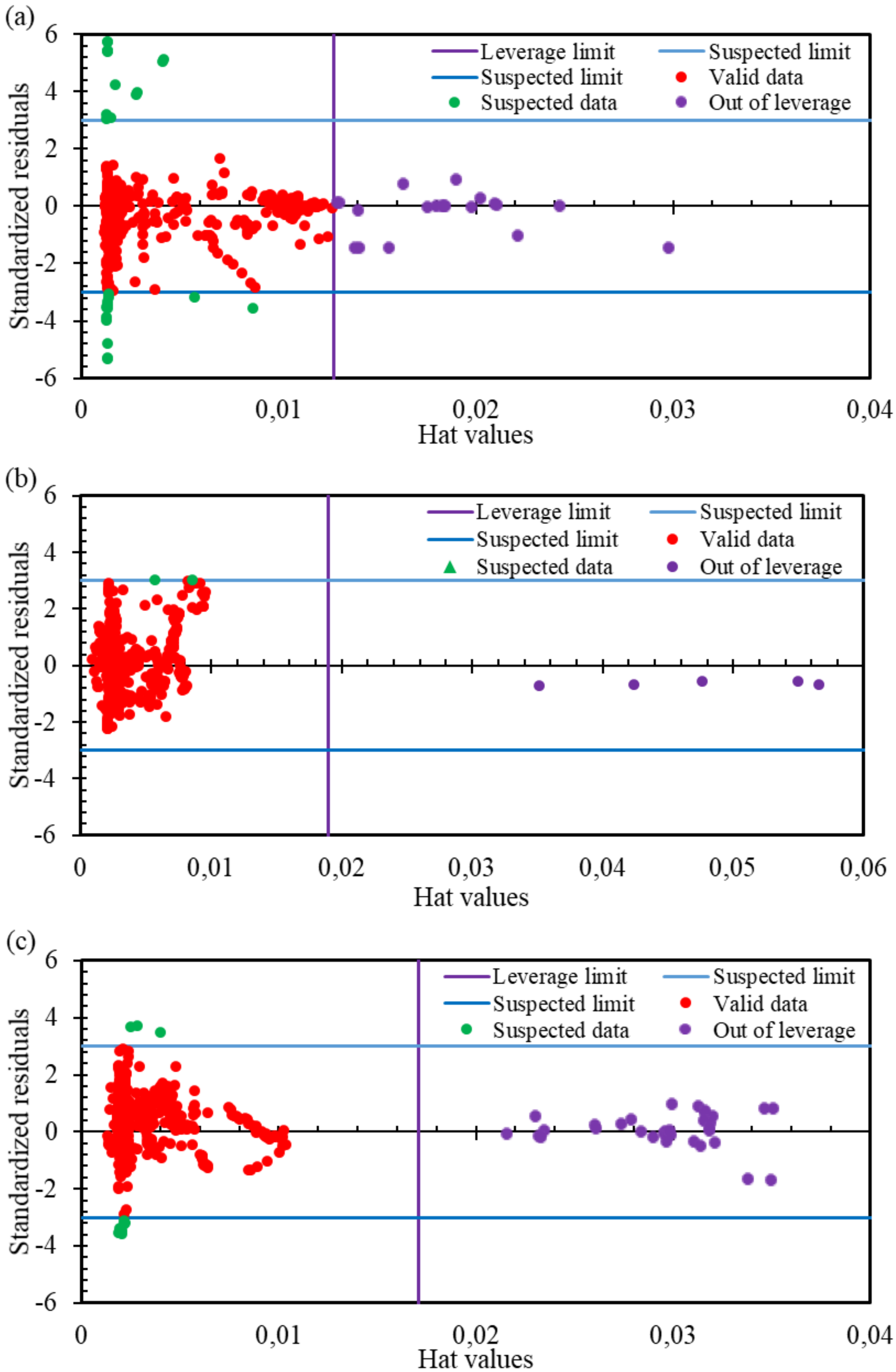

Fig. 6. Williams plots for the proposed GRU model to identify the applicability domain. Subfigures (a), (b), and (c) correspond to Wells 1, 2, and 3, respectively.

4.4. Limitations and improvements

The performance of LSTM and GRU models in predicting BHP changes during UBD operations highlights their potential applicability across various wells and operational conditions. However, the models occasionally tend to slightly overestimate or underestimate BHP for some instances, possibly due to data quality issues, measurement inaccuracies, or other factors influencing BHP measurements. The wells drilled with UBD in this study are approximately 1,000 meters in length. This relatively short drilling length, combined with the use of data extracted from graphs rather than direct data logs, limits the amount of data available for analysis. A more extensive dataset could potentially improve the accuracy of the developed models. Future research should adopt the methodology presented in this study, with a focus on collecting additional real-time data, refining feature engineering, and addressing data quality issues to enhance model robustness and reliability across diverse drilling environments.

5. Conclusion

This study evaluated LSTM and GRU models for predicting bottomhole pressure changes during underbalanced drilling operations across multiple wells. The findings demonstrate that both LSTM and GRU models exhibit promising accuracy, with the GRU model slightly outperforming the LSTM model in terms of MAPE and RMSE values. Graphical analysis of the GRU model further reveals a strong agreement between predicted and actual BHP across multiple wells, indicating the model's robust generalization capacity. These results underscore the effectiveness of the models in forecasting BHP dynamics, which are critical for maintaining underbalanced conditions and mitigating reservoir damage. Challenges such as limited data quantity and variability in operational conditions underscore the need for future research to focus on expanding dataset sizes and integrating real-time data feedback. These efforts aim to enhance model generalizability and reliability, ultimately supporting more accurate and proactive management of BHP during UBD operations. In conclusion, while LSTM and GRU models show considerable promise in predicting BHP changes, ongoing advancements in machine learning techniques and data handling strategies are essential to maximize their utility in optimizing UBD efficiency and safety.

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