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DEVELOPING A NEURAL NETWORK MODEL TO PREDICT THE OPTIMAL MINIMUM FLOW RATE FOR EFFECTIVE HOLE CLEANING

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The object of the study is effective well cleaning during drilling. The subject of the study is the development of a machine learning model based on a neural network for predicting the optimal minimum drilling fluid flow rate. The challenge is the need to improve well cleaning efficiency to prevent stuck pipes and the associated downtime and costs.

During the study, a neural network model was developed and tested to predict the minimum flow rate for cleaning wells. The model was trained and tested on data showing its high accuracy and reliability. The mean square error (MSE) reached 0.019169 for LSTM and 0.0828 for GRU, indicating the accuracy of the predictions. Neural network architectures such as Long-Short Term Memory (LSTM) and Gated Recurrent Unit (GRU) were used to efficiently process time series of data and consider long-term dependencies.

The results are explained using advanced neural network architectures and machine learning algorithms, which made it possible to achieve good accuracy of predictions. These architectures enable efficient model training on large amounts of data, allowing complex dependencies and influencing factors to be considered.

Distinctive features of the results include good accuracy of predictions and the ability to use the model in real-world conditions. The model demonstrates good performance and reliability in predicting the minimum flow rate.

The results of the study can be used to optimize the processes of well drilling. Practical applications include using the model to predict the optimal minimum flow rate in various conditions, which will reduce the risks of stuck pipes and increase the efficiency of drilling operations. The model can be integrated into existing monitoring and control systems for drilling processes to improve their performance

Keywords: well drilling, hole cleaning, pipe sticking prevention, neural network, machine learning, minimum flow rate

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1. Introduction

The topic of wellbore cleaning during drilling operations is of critical importance to the oil and gas industry, particularly due to the significant impact of stuck pipe incidents. Stuck pipe is a common, unplanned event that accounts for at least 25 % of non-productive time (NPT), equating to the annual cost of two drilling years [1]. The duration of a stuck pipe incident can vary significantly, from a few days to more than a month, during which additional repair costs-such as tool retrieval, lost tools, and workaround expenses-are often incurred [2]. Therefore, optimizing wellbore cleaning to prevent such incidents is not only relevant but essential for reducing operational costs and improving drilling efficiency.

Ineffective cleaning of the wellbore from drill cuttings is one of the primary causes of stuck pipe. This issue can arise at various stages of drilling, particularly in horizontal and directional wells. The efficiency of cuttings transportation depends on a complex interplay of variables, including hole inclination, angle, hole and drill pipe diameter, drill pipe rotation speed, drill pipe eccentricity, penetration speed, the characteristics of the cuttings (e. g., particle size and rock porosity), and the properties of the drilling fluid (e. g., flow rate, fluid velocity, flow regime, drilling fluid type, and non-Newtonian fluid rheology). Key factors for optimizing well cleanup include a sound drilling plan, appropriate mud properties, and extensive drilling experience [3–5].

Despite ongoing research into well cleaning techniques, several unresolved challenges remain. A key area of concern is the optimization of drilling fluid parameters such as density, viscosity, and transport speed to ensure efficient removal of cuttings. Numerous studies have emphasized the importance of developing and applying new models and techniques for predicting optimal drilling fluid parameters. For instance, in this work [4] demonstrated the significance of drilling fluid parameters for effective cleaning of vertical wells, while authors [6] highlighted the role of drilling fluid rheology and annulus velocity in well cleaning under various conditions. Furthermore, this study [7] combined Larsen models and Moore's correlation to predict the minimum flow rate required for cuttings removal in wells with different inclinations. Authors [8] used artificial neural networks to model well conditions and predict cuttings concentrations, showcasing the potential of machine learning to improve prediction accuracy.

However, significant challenges persist in optimizing well cleaning processes, particularly in the face of complex drilling conditions, the high costs associated with research and field experiments, and the limitations of existing models and correlations, which may not fully account for the complexities encountered in real-world drilling scenarios.

As drilling operations become more complex and efficiency requirements increase, efficient well cleanup becomes critical to reduce costs and prevent accidents. Traditional methods of calculating the minimum flow rate often fail to cope with the multitude of factors and complex nonlinear dependencies. In this regard, the use of machine learning, in particular neural networks, is becoming a relevant technology to address this problem, providing more accurate predictions and improving the efficiency of drilling processes.

2. Literature review and problem statement

In this paper [4] authors discuss the challenges associated with effective wellbore cleaning in vertical drilling. It is shown that wellbore cleaning efficiency is highly dependent on several parameters such as drilling mud density, viscosity, pour point, and transport velocity. The study highlights that inadequate wellbore cleaning can lead to serious operational problems including slower drilling rates, increased costs, and the risk of pipe jamming due to accumulation of drilled particles in the annulus and on the borehole walls. This paper highlights the relationship between drilling mud properties and wellbore cleaning efficiency. However, unresolved challenges include the precise optimization of fluid properties under varying conditions, such as borehole diameter, inclination, and fluid dynamics in different well configurations.

This paper [9] discusses the application of artificial intelligence to predicting drilled particle concentrations in non-vertical wells. It is shown that machine learning models can significantly improve the accuracy of predicting drilled particle transport, however, challenges remain in integrating these models in real-time and taking into account complex conditions at depth. The study discusses the use of artificial intelligence in predicting drilled particle concentrations but identifies gaps in real-time integration of AI models, particularly under complex conditions at greater depths.

This study [10] discusses the use of mud flushes to improve wellbore cleaning efficiency in non-vertical wells. It has been shown that flushes can effectively remove drilled solids, but their effectiveness depends on factors such as fluid properties, flow rate, and borehole geometry. The study highlights the unresolved issues associated with optimizing flush parameters for different borehole conditions. This work examines the impact of mud flushes on wellbore cleaning. While the study provides insight into the effectiveness of flushes, the unresolved challenge is optimizing flush parameters for various well conditions and fluid properties.

This paper [11] presents comprehensive analyses of wellbore cleanouts in large and high-angle wells. These studies show that effective wellbore cleanout under these conditions requires careful management of drilling fluid properties and flow rate. They also highlight the difficulties in maintaining effective wellbore cleanout as borehole diameter and inclination increase, leading to increased drilled solids concentrations and potential plugging. The research focuses on cleaning in large and high-angle wells but points out the difficulty in maintaining cleaning efficiency as borehole inclination and diameter increase, leading to unresolved challenges in managing increased cuttings concentration.

This paper [12] discusses the implementation of intelligent action planning and automation in well construction operations. It is shown that automated systems can improve wellbore cleanout efficiency by dynamically adjusting drilling parameters in response to real-time data. However, the complexity of developing and integrating such systems presents significant challenges. However, significant challenges remain in developing and integrating intelligent systems capable of making real-time adjustments to drilling parameters based on dynamic conditions.

This study [13] explores the use of machine learning models to optimize wellbore cleanout parameters. It is shown that these models can provide accurate predictions and adjustments to drilling fluid properties, but their application is still limited by the need for large amounts of data and computational resources. Although promising, challenges persist in the need for large datasets and computational resources to improve model accuracy and practical application.

This review [14] provides a detailed analysis of wellbore cleanout challenges and strategies in horizontal wells. The review highlights the importance of understanding the interactions between drilling fluids and wellbore conditions and identifies gaps in current knowledge that need to be addressed through further research. This paper identifies gaps in understanding the interaction between drilling fluids and wellbore conditions in horizontal wells, however further research is needed to optimize drilling fluid properties across diverse well conditions.

This study [15] discusses the development of adaptive systems for real-time wellbore cleanout problem detection. The study shows that adaptive algorithms can significantly improve wellbore cleanout problem detection and resolution, but their effectiveness depends on the quality of real-time data and the robustness of the underlying models. However, the challenge lies in ensuring the robustness of these algorithms and improving the quality of real-time data.

This paper [16] presents an automated model for real-time wellbore cleanout performance evaluation. The study demonstrates that such models can significantly improve the rate of penetration (ROP) by optimizing drilling parameters and making timely interventions based on real-time data. The implementation of these models shows potential to reduce operating costs and improve drilling efficiency, but further research is required to refine them and validate their effectiveness in various drilling scenarios. Even though this study presents a real-time model for evaluating wellbore cleaning performance, yet there are unresolved challenges in refining the model's accuracy for various wellbore conditions and validating its effectiveness in diverse field scenarios.

Despite advances in wellbore cleanout, there remain unresolved issues related to the optimal combination of drilling fluid properties, flow rates, and real-time adjustments required to maintain effective wellbore cleanout under varying wellbore conditions. The reasons for these unresolved issues can be attributed to several factors, including:

– objective difficulties associated with accurately modeling and predicting fluid dynamics in real-world drilling conditions;

– principles the general impossibility of achieving a universal solution due to the variability of wellbore conditions and drilling environment;

– high costs of implementing advanced drilling fluid systems and monitoring technologies, making complex studies and adjustments in real time economically challenging.

One option to overcome these difficulties may be the integration of machine learning and artificial intelligence methods for dynamic optimization of drilling parameters. This approach is explored in several papers, where the authors propose to use machine learning models to predict and adjust drilling fluid properties in real time, which improves well cleaning efficiency and reduces operational risks. However, the implementation of such technologies is in the early stages, and further research is required to improve them and test their effectiveness in various drilling scenarios.

All this allows to state that it is worthwhile to conduct a study devoted to the development of a comprehensive real-time well cleaning optimization system for drilling operations. This research will focus on integrating advanced computational models, real-time data collection and machine learning techniques to create a robust system for predicting and adjusting drilling parameters, thereby improving well cleaning efficiency and reducing operational risks.

3. The aim and objectives of the study

The aim of this study is to predict the optimal minimum flow rate for effective hole cleaning in drilling operations, thereby preventing pipe sticking.

To achieve this aim, the following objectives are accomplished:

– to create a model that accurately predicts the minimum flow rate of drilling mud necessary for efficient hole cleaning;

– to validate the accuracy and reliability of the developed neural network using real-world field data.

4. Materials and Methods

4. 1. Object and hypothesis of the study

The object of the study is effective well cleaning during drilling. The subject of this study is the models themselves and the process of model creation.

The main hypothesis of the study is to possibility of building a neural model or models to predict the minimum flow rate for cleaning the borehole. The main assumption in the dataset that was used to train the models. The logical question here would be “will the model be universal for all wells or will it be only for wells from one field?”. The fact is that depending on the field, the physical properties of the rock may differ from each other, and accordingly the minimum flow rate will be quite different. Another of the assumptions in the data that were collected in one dataset. For the model to be able to train and find relationships between the proposed data and the data we want to get, it is necessary that these data can be different from each other, otherwise the model may be trained incorrectly. Therefore, it is possible to select those data that differed from well to well, but the assumption is that these data may not be indirectly or at all related to those characteristics that really affect the minimum flow rate This is a simplification. Another of the model training simplifications was to reduce the data prediction range from 0 to 1 so that the model could better and more accurately predict the behavior of the curve on the graph.

In this study, various neural network architectures were employed to predict the optimal minimum flow rate of drilling fluid required for effective wellbore cleaning. The architectures were selected based on their ability to handle complex time-series data and nonlinear relationships, which are characteristic of drilling operations. The primary architectures used in this research are Feed-Forward Neural Networks (FNN), Long Short-Term Memory (LSTM) networks, and Gated Recurrent Unit (GRU) networks.

Feed-Forward Neural Network. Classification. Using this neural network architecture, let’s aim to identify potential complications in the flow rate during drilling. To achieve this, the output data to range from 0 to 1 was configured, where 0 indicates minimum possible flow rate for hole cleaning and 1 indicates the maximum possible flow rate for hole cleaning.

Let’s utilize the leaky ReLU activation function for the input and hidden layers, and the sigmoid function for the output layer. Additionally, the binary cross-entropy loss function and the Adam optimizer to train the model were employed. The loss function measures the discrepancy between the model’s predictions and the actual values, with the objective of minimizing this error during training.

Selecting the appropriate loss function depends on the specific machine learning task, whether it is classification, regression, or another type of problem. Similarly, choosing the right optimizer is crucial, as it updates the model’s weights based on the calculated gradients of the loss function, thereby minimizing the loss.

There are several optimizers available, each with distinct characteristics. Some of the most commonly used optimizers include Stochastic Gradient Descent (SGD), Adam, and RMSprop, among others. Each optimizer has its own advantages and disadvantages depending on the nature of the problem and the structure of the model.

Using binary cross-entropy to create a classification model is nothing more than an optimizer for the model. The classification model in this case is not used as a way to classify, say, a bad well cleanup from a good one. Moreover, our task implies obtaining data of fluid flow rate from depth and other various factors, i.e. there is no classification. The use of classification models was needed only to reduce the range of data that the model has to predict. For example, if to use an ordinary model, it will need to predict numbers from 0 to infinity, since the fluid flow rate can be anything but negative. However, when using a classification model, it is possible to narrow the range of data to be predicted, from 0 to 1. Then the model can be trained to predict the data. However, this is still not classification in our understanding, because the data are not 0 and 1, but from 0 to 1, i. e. they can be 0.75, 0.33, 0.553235 and so on. However, you may ask: “but how are you going to use this data for real cases, you are not going to use 0.66 liters to clean a well”. For this purpose 2 more models were created that predict the minimum possible flow rate and the maximum possible flow rate (more precisely scroll down below, so everything is described in detail), and then by matching that 0 from the classification model is the minimum predicted flow rate, and 1 is the maximum predicted flow rate.

The following Fig. 1 illustrates the number of neurons and layers used in the model.

The binary cross-entropy loss function was utilized, which is appropriate for binary classification tasks. The

Adam optimizer, known for its efficiency in handling sparse gradients and its suitability for large datasets, was used to minimize the loss function.

To get accuracy results about our model we need to use the model.evaluate method and the mean_squared_error method from the sklearn library.

As for precision and recall metrics, they are most often used for tasks where it is necessary to find certain classes – i.e. classification task. There is no classification task, and besides, the obtained data is continuous, i.e., it can be in the range from 0 to 1, not 0 and 1. This was explained in the paragraph above.

Feed-forward neural network (all real numbers). This version of the FNN was developed to predict continuous, real-valued outputs instead of binary classifications, providing precise flow rate predictions.

Fig. 2 shows visualization of the model.

As illustrated, the model consists of four dense layers. The first layer contains 11 input nodes, followed by the second layer with 8 nodes, the third layer with 16 nodes, and finally, a single output node.

In the compile function, let's use the mean squared error (MSE) as the loss metric and Adam as the optimizer, with a learning rate set to 0.1. The learning rate is a crucial tunable parameter in the optimization algorithm, determining the step size at each iteration as the model moves toward minimizing the loss function.

The learning rate plays a significant role in finding the optimal weights and minimizing the loss for the model. If the learning rate is set too low, the model would require an exceptionally long time to train, as the weight updates would be minimal, potentially causing the model to stall in its training process. On the other hand, if the learning rate is too high, the model might "overshoot" the global minimum of the loss function, leading to undertraining or overtraining.

Through experiments with various learning rates, it is possible to determine that a learning rate of 0.1 is optimal for training this model, providing a good balance between training time and model accuracy.

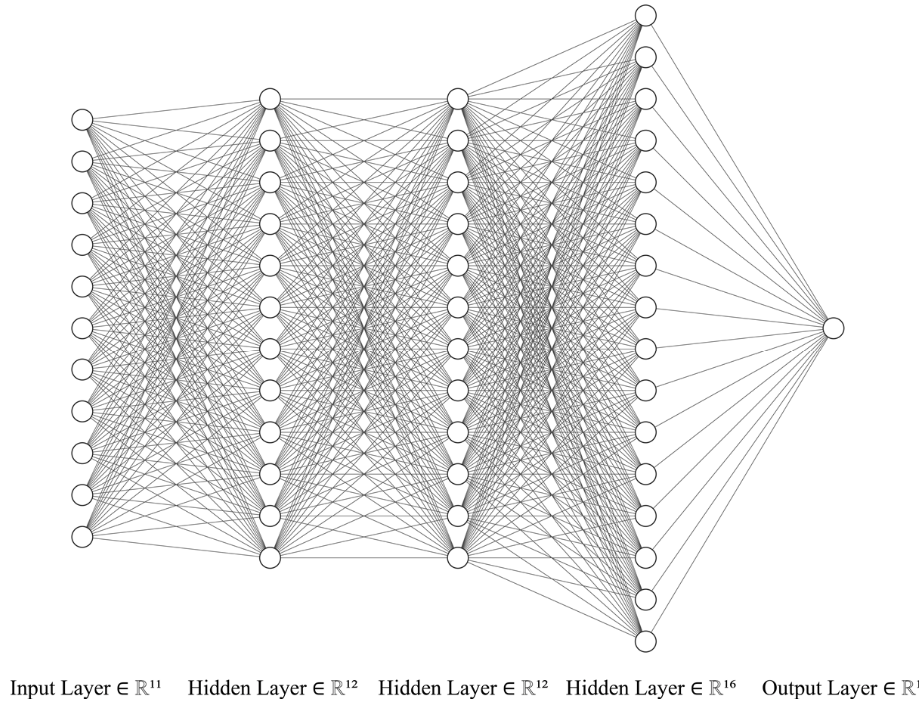


Fig. 1. Forward neural network architecture (output range from 0 to 1)

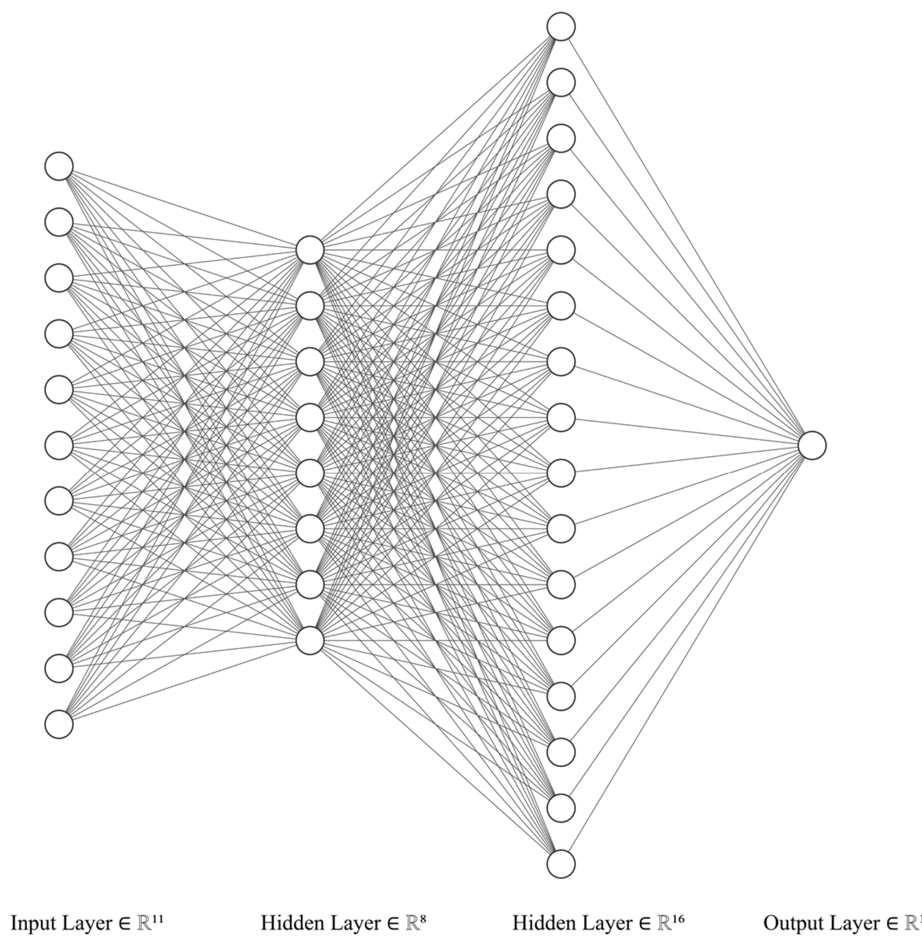


Fig. 2. Forward neural network architecture

Long-short term memory (LSTM). Recurrent Neural Network. The LSTM network was implemented to capture long-term dependencies in the time-series data, which are crucial for accurately predicting flow rates over extended periods of drilling operations.

Recurrent neural network – a type of neural network where the connections between elements form a directed sequence. This makes it possible to process series of events in time or sequential spatial chains. Unlike multilayer neural networks, recurrent networks can use their internal memory to process sequences of arbitrary length. Therefore, RNNs are applicable in such tasks: speech recognition, time-series prediction, etc. [17]. Fig. 3 shows how recurrent neuron looks.

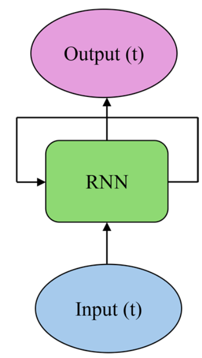


Fig. 3. A single recurrent unit

In the diagram above, the fragment of the neural network takes the input value $input_t$ and returns the value $output_t$. The presence of feedback allows to transfer information from one step of the network to another.

A recurrent network can be thought of as multiple copies of the same network, each passing information to a subsequent copy. This is what happens if to deploy a recurrent network. The next Fig. 4 shows the disclosed recurrent neuron.

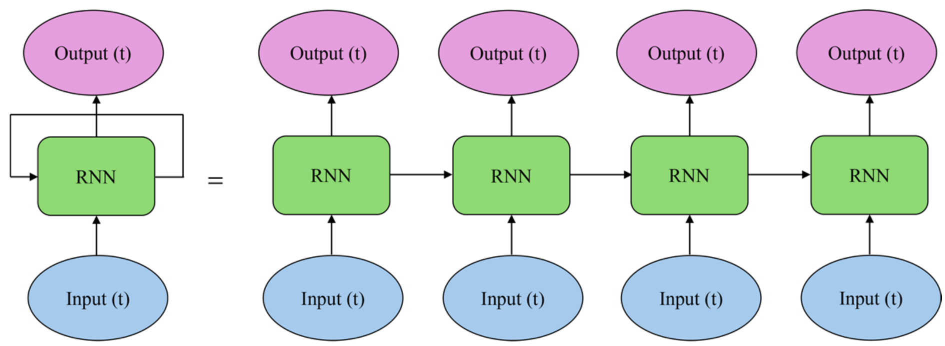


Fig. 4. The Disclosed Recurrent neural network

The next figure, Fig. 5, illustrates the design of the LSTM neural network.

To create the LSTM network, it is possible to start with 11 LSTM units. The output from the LSTM layer is then passed to a traditional Deep Neural Network (DNN), and finally, it is possible to obtain the output through a sigmoid activation function. Since it is possible to use a sigmoid activation function in the output node, our outputs will range from 0 to 1.

Normalization across the FNN [0:1], LSTM, and GRU models was implemented. When predicting data, the results are denormalized from the 0 to 1 range back to their real-world values. In parallel to the main neural networks, two additional neural networks were developed to predict the minimum and maximum possible flow rates. These values are then used for denormalization, ensuring that our predictions reflect the true range of flow rates from the minimum to the maximum possible values.

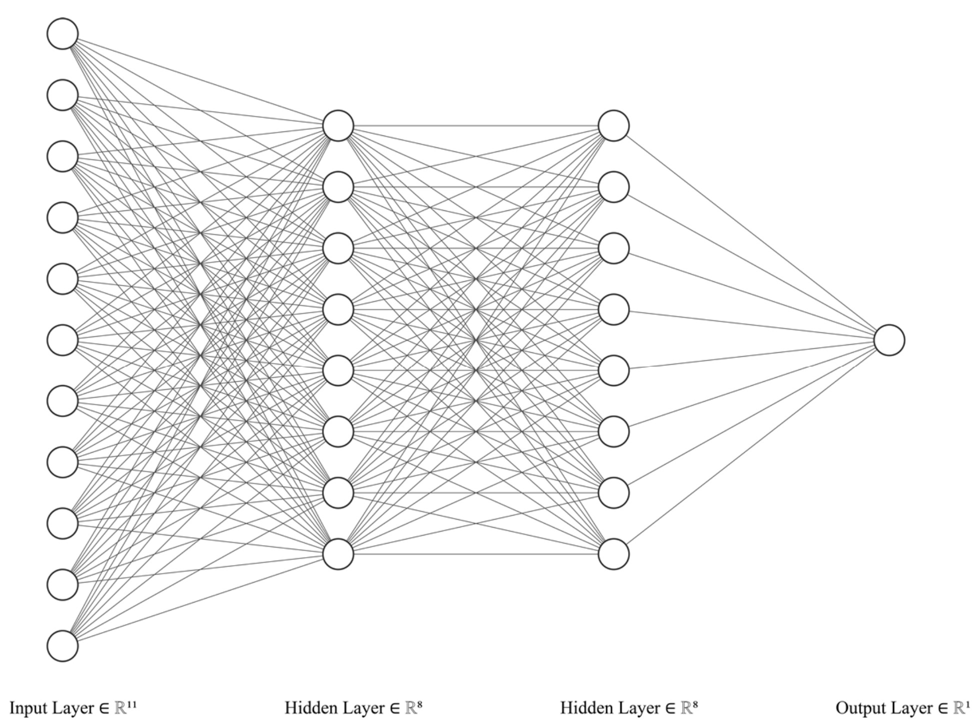


Fig. 5. Long-short term memory network architecture

For compiling the model, let's select RMSprop as our optimizer with a learning rate of 0.01, and use Mean Squared Error (MSE) as the loss function.

It is possible to train the model for 500 epochs with a batch size of 8. Through experimentation, it was found that 500 epochs provided the optimal balance, as the model consistently performed best around this point. Although with 1000 and 1500 epochs were also experimented, it was not possible to observe significant improvements beyond 500 epochs.

Gated recurrent unit (GRU) Networks. The GRU network was chosen as a simpler and faster alternative to LSTM while still maintaining the ability to process sequential data effectively.

A gated recurrent unit (GRU) is a type of recurrent neural network (RNN) that is similar to the Long Short-Term Memory (LSTM) architecture. Developed in 2014, GRU was designed to simplify and speed up the training process compared to LSTM, while still maintaining much of its effectiveness, particularly in data sequence processing tasks.

Unlike LSTM, GRU does not have a separate long-term cell state. Instead, GRU uses update and reset gates to modulate the past state and new input data. At each step, the hidden state is updated, allowing information to propagate throughout the network.

Similar to LSTM, GRU does not utilize a distinct memory cell. Instead, it updates the hidden state directly. The model determines how much of the previous hidden state should be retained using an update gate, which integrates new and prior information.

The update gate creates a new hidden state based on the data received from the reset gate, which controls how much of the past state is needed for the current input. This mechanism provides GRU with enhanced control over the flow of data.

To update its state, GRU employs various mathematical operations, such as the sigmoid function for the gates and the hyperbolic tangent function to generate new state candidates. These operations enable GRU to manage the data flow dynamically and effectively [8].

Fig. 6 below illustrates the key differences between Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU) architectures, highlighting the distinct characteristics and functionalities of each model.

Fig. 7 illustrates the design of the GRU network.

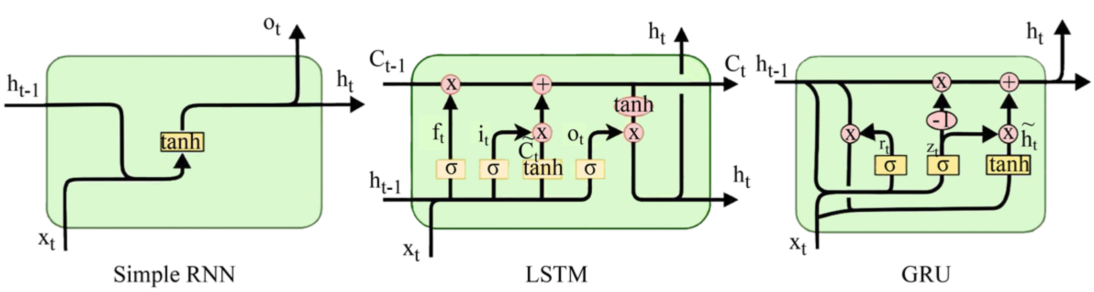


Fig. 6. Comparison of recurrent neural network vs. long-short term memory vs. gated recurrent unit [14]

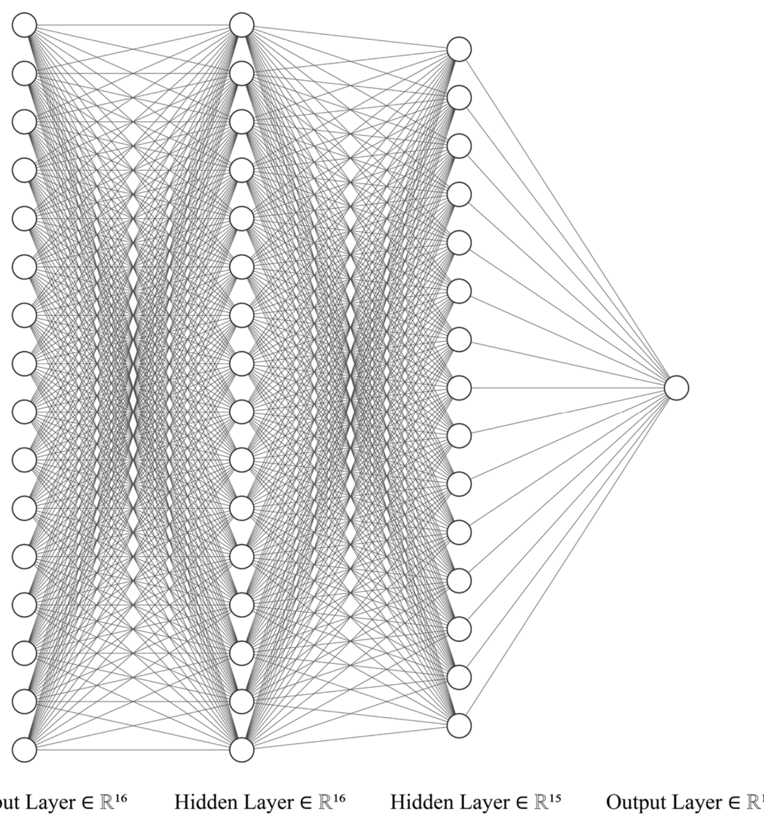


Fig. 7. Gated recurrent unit network architecture

This figure highlights the similarities in architecture between GRU and LSTM, showcasing how both models are structured to efficiently handle sequential data while addressing challenges like long-term dependencies.

The GRU architecture shown above has been reduced by a factor of 4, as displaying the actual number of neurons would have made the illustration too large to fit properly.

For compiling the model, binary cross-entropy was selected as the loss metric and Adam as the optimizer, with a learning rate of 0.0001.

4. 2. Data preparation and training

The data used for training the neural networks was sourced from both real-world field measurements and simulated data representative of typical drilling operations. The dataset included key drilling parameters such as flow rate, wellbore depth, drill pipe rotation speed, and properties of the drilling fluid, all of which influence the efficiency of wellbore cleaning.

Data normalization. To ensure that all input features contributed equally to the model's learning process, the data was normalized. This step was crucial for preventing any single feature from dominating the learning process due to its scale. The normalization process involved scaling the input data to a range between 0 and 1, which is particularly important for neural networks as it speeds up convergence and improves performance.

At the bottom is the equation used to convert the normalized values to actual values:

$$x=\frac{x_i-x_{\min}}{x_{\max}-x_{\min}}, \qquad (1)$$

where $x_{\min}$ – 11.73; $x_{\max}$ – 36.06; x_i – predicted (range 0–1).

The $x_{\min}$ and $x_{\max}$ are the values that were predicted by the two separate neural networks that are trained to find the maximum possible and minimum possible flow rate for the given depth.

Training process. The models were trained using a supervised learning approach, where the model weights were iteratively updated using the backpropagation algorithm. Different numbers of epochs and batch sizes were employed to optimize the training process. After extensive experimentation, the best results were achieved using 500 epochs and a batch size of 8 for the LSTM model, as this configuration provided a good balance between training time and model performance. The training data was split into training and validation sets, where the model was trained on the training set and validated on the validation set to ensure that it could generalize to new, unseen data.

Model evaluation. During training, the model's performance was continuously monitored using loss values. Let's aim to minimize the loss function as much as possible to improve the model's predictive accuracy. After training, the model's performance was further evaluated using a separate test set, which was not involved in the training process. This holdout validation approach ensured that the model's predictive capabilities were assessed in a realistic scenario.

4. 3. Model evaluation metrics

The performance of the neural networks was evaluated using several key metrics, each chosen to provide insights into different aspects of model performance.

Mean squared error (MSE). MSE was used to quantify the average squared differences between the actual and predicted values [18]. It is a standard metric for regression tasks, where lower MSE values indicate better predictive accuracy. For the models developed in this study, MSE was particularly critical in assessing how well the models could predict flow rates that are essential for effective wellbore cleaning:

$$MSE=\frac{1}{n}\sum_{1}^{n}\left(y_{actual}-y_{redicted}\right)^2, \qquad (2)$$

where n – number of observations; y_{actual} – actual represents the actual values; $y_{predicted}$ – predicted represents the predicted values.

Basically, the lower value of MSE the better.

Accuracy. Accuracy was calculated as the ratio of correctly predicted instances to the total number of instances. This metric was particularly relevant for the classification tasks handled by the Feed-forward neural network [0:1]. While accuracy is less commonly used in regression tasks, it was still computed to provide a general sense of the model's ability to make correct predictions:

$$Accuracy=\frac{y_{predicted}}{y_{actual}}. \qquad (3)$$

Loss. The loss function provided a direct measure of how well the model's predictions matched the actual values during training. Lower loss values indicate that the model is making fewer errors. For each neural network, the loss during training was monitored to ensure that the model was learning effectively and not overfitting to the training data.

5. Results predicting the optimal minimum flow rate for effective hole cleaning

5. 1. Results of models

Feed-Forward Neural Network [0:1]. The Feed-Forward Neural Network (FNN) designed for binary classification performed adequately in predicting potential complications in flow rates. The model achieved an MSE of 0.023135, indicating a relatively low error margin in its predictions. The accuracy was recorded at 44 %, which, while modest, is reasonable considering the binary nature of the task. The loss value was observed to be 0.059, suggesting that the model's predictions were fairly close to the actual outcomes. Fig. 8 illustrates the validation results for the feed-forward neural network [0:1], highlighting the distribution of predicted versus actual values.

As seen in the Fig. 8, the model's predictions are generally consistent with the actual data, although there is room for improvement in accuracy.

Feed-forward neural network (all real numbers). The feed-forward neural network (all real numbers) was tasked with predicting continuous values for the flow rate. This model exhibited a significantly higher MSE of 19.1819, indicating a larger deviation from actual values. This suggests that predicting real-valued outputs in this context is challenging, likely due to the complexity of the underlying data and the limitations of the model in capturing all influencing factors. The loss was recorded at 0.0, which is unexpected and suggests potential issues with model training or data preprocessing. Fig. 9 provides a visual representation of the Feed-Forward Neural Network's performance, showing the comparison between predicted and actual flow rates.

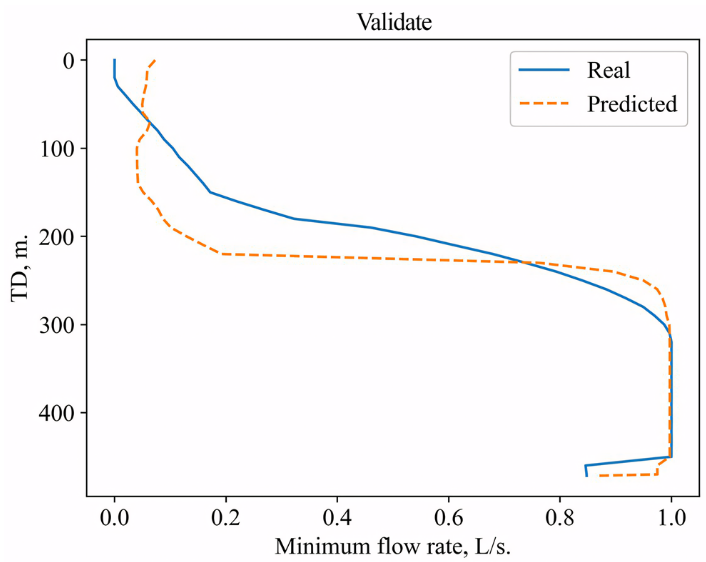


Fig. 8. Feed-forward neural network [0:1] results

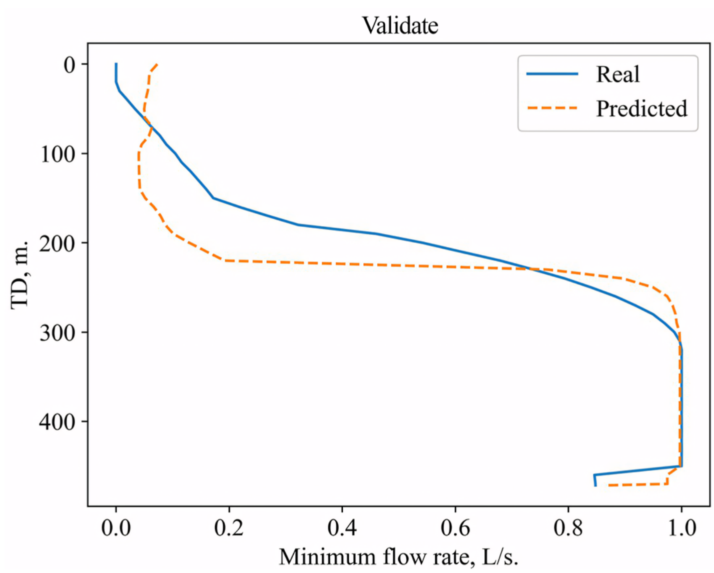


Fig. 9. Feed-forward neural network plot

The Fig. 9 demonstrates that while the model can follow the general trend of the data, it struggles with precise predictions, particularly in regions with complex flow dynamics.

Long-short term memory (LSTM). The Long-short term memory (LSTM) network, designed to handle sequential data, performed well in predicting the flow rates. The model achieved an MSE of 0.019169, one of the lowest among all models tested, indicating high predictive accuracy. The loss value was similarly low at 0.019, reflecting the model's ability to effectively capture long-term dependencies in the data. Fig. 10 displays the LSTM model's performance, showing the predicted values alongside the actual values.

The tight alignment between the two sets of values highlights the LSTM's strength in handling time-series data, making it a robust choice for real-time applications in drilling operations.

Gated recurrent unit (GRU). The gated recurrent unit (GRU) model, designed as a more streamlined alternative to LSTM, showed moderate performance [19]. The MSE for the GRU model was 0.0828, which is higher than that of the LSTM but still within an acceptable range for predictive tasks. The loss value was 0.5297, indicating that while the model is capable, it may not capture all the nuances of the drilling data as effectively as the LSTM. Fig. 11 provides a visual summary of the GRU model's results, comparing the predicted flow rates with the actual values.

The Fig. 11 shows that the GRU model generally follows the data trends but with less precision than the LSTM model, particularly in complex regions of the dataset.

Combined neural networks analysis. To enhance prediction accuracy, the outputs from all neural networks were combined. This approach aimed to create a more generalized model by averaging the predictions from the different networks. The combined model was found to smooth out the errors observed in individual models, leading to more reliable predictions across the depth range. Fig. 12 shows the process of denormalization applied to the network outputs, translating the normalized predictions back into real-world values.

The Fig. 12 clearly depicts the transition from model output to actionable data, which can be directly applied in drilling operations.

Fig. 13 consolidates the predictions from all the neural networks into a single plot, allowing for a direct comparison of their performances. The plot indicates that while individual models may show variations, their combined output provides a more consistent and reliable prediction.

Finally, Fig. 14 presents the generalized plot created by averaging the outputs of all neural networks.

By obtaining the results from all neural networks, denormalizing the results and then creating the combining all models into one Fig. 15 and then creating the generalized plot in Fig. 16.

This final model is recommended for use in drilling operations due to its balanced performance, capturing both the general trend and specific details across the entire dataset.

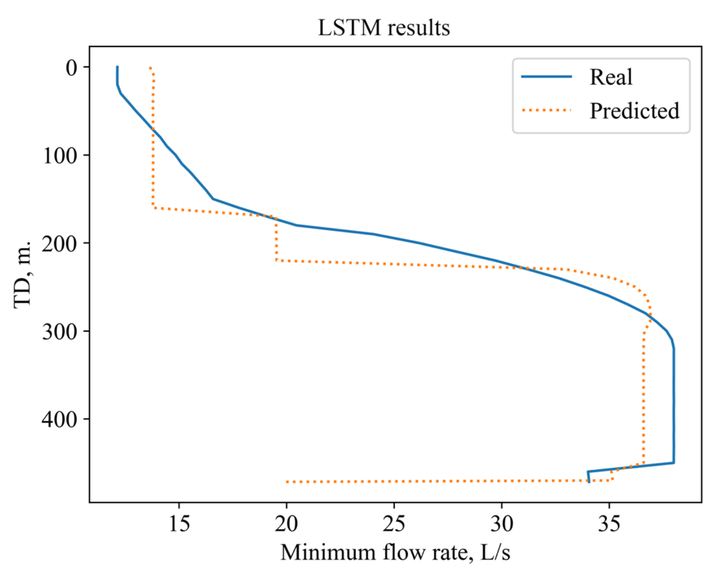


Fig. 10. Long-short term memory (LSTM) plot

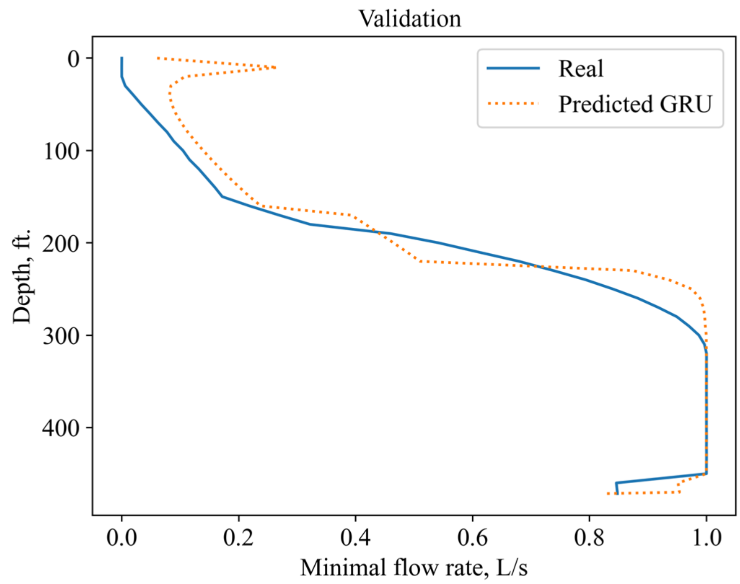
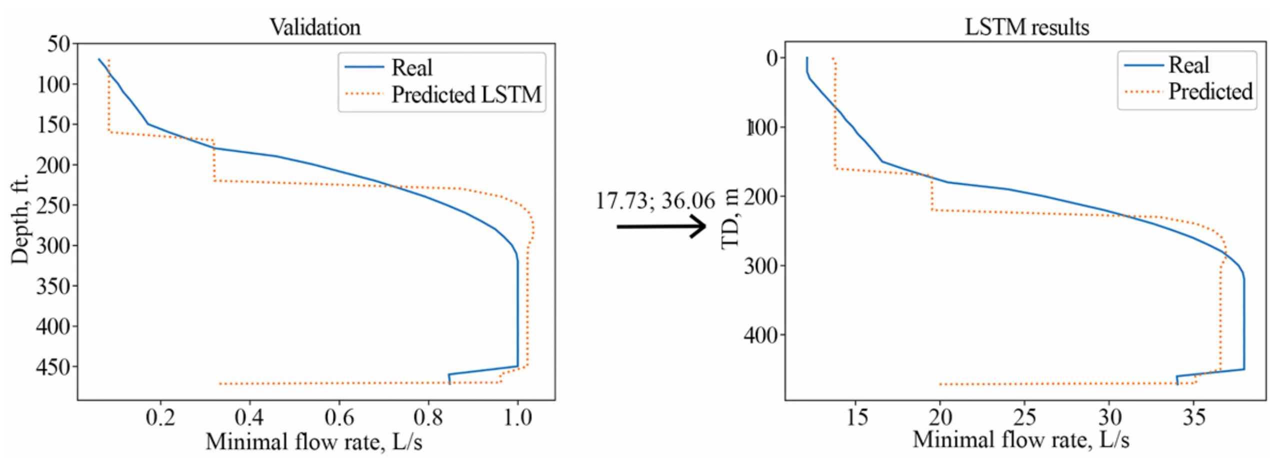


Fig. 11. Gated recurrent unit (GRU) plot



a *b*

Fig. 12. Denormalization process: *a* – prediction plot [0:1] before; *b* – prediction plot after

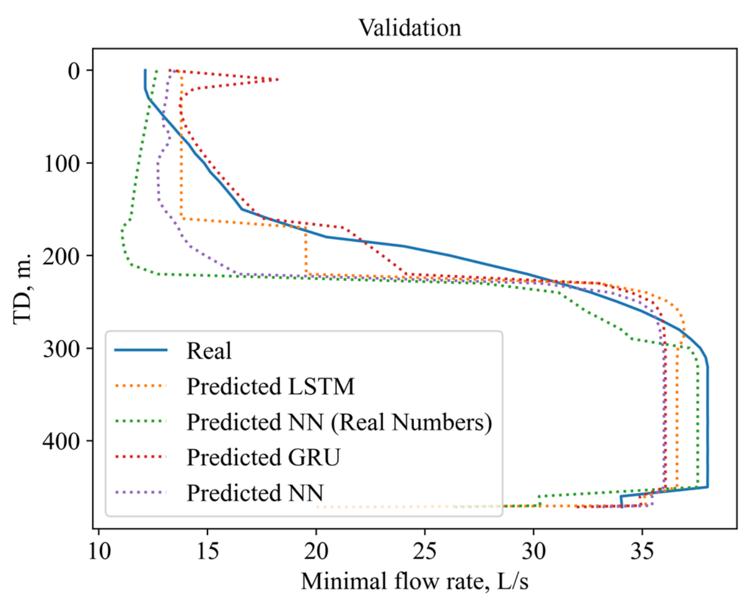


Fig. 13. All Neural Networks combined

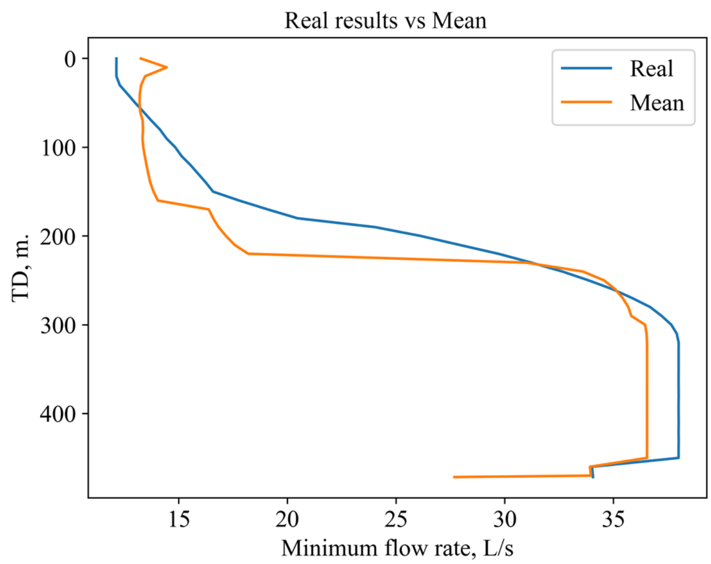


Fig. 14. Generalized plot of neural networks

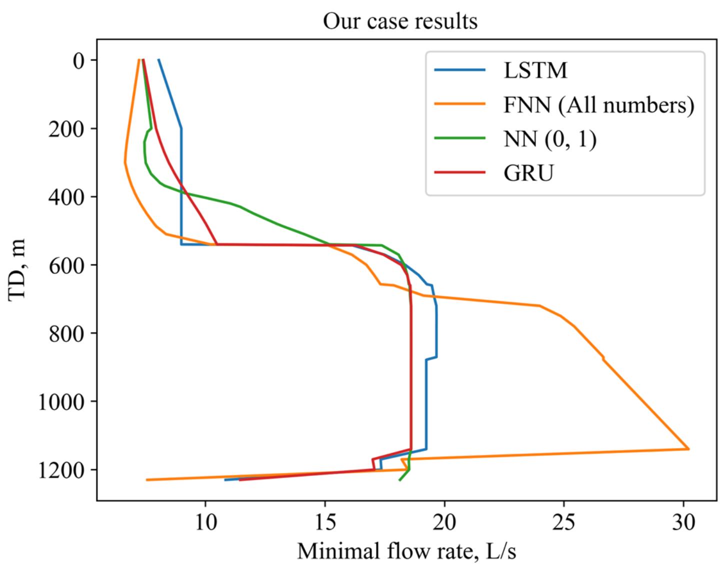


Fig. 15. Results of artificial well

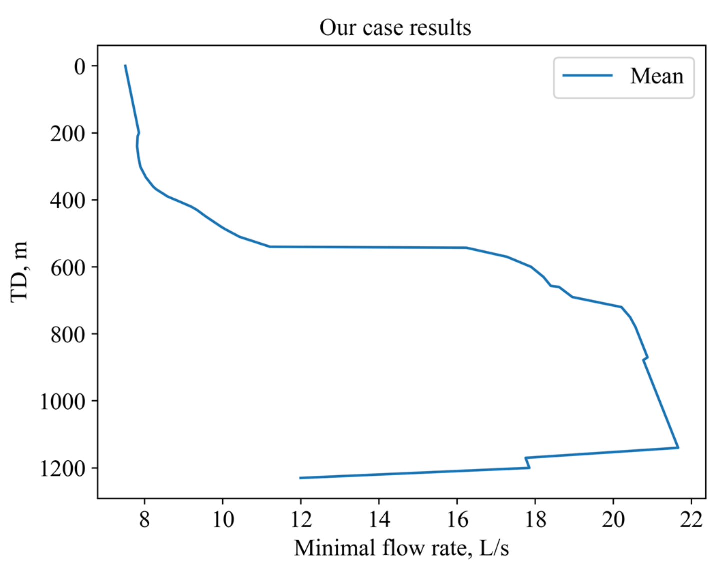


Fig. 16. Generalized plot of neural networks

5. 2. Validation of neural network accuracy using real-world data

To evaluate the accuracy of the neural networks, the dataset was split into training and test sets. The test set was used to validate the models, ensuring that their predictions were accurate and generalizable to new data. The following tables present the validation results for each neural network model.

Feed-forward neural network [0:1]. Table 1 provides the validation results for the feed-forward neural network [0:1]. The model's performance is assessed using metrics such as mean squared error (MSE), accuracy, and loss.

Table 1

MSE, accuracy, and loss values for FFNN [0:1]

Metric	Value
MSE	0.023135
Accuracy	0.44
Loss	0.059

These metrics indicate the model's ability to predict binary outcomes related to flow rate complications.

Feed-forward neural network (all real numbers). The validation results for the feed-forward neural network designed to predict continuous values are shown in Table 2.

Table 2

MSE, accuracy, and loss values for FFNN (all real numbers)

Metric	Value
MSE	19.1819
Accuracy	19.1819
Loss	0.0

This Table 2 includes the MSE, accuracy, and loss values, reflecting the model's performance in predicting real-valued flow rates.

Long-short term memory (LSTM) network. Table 3 presents the validation results for the LSTM model.

Table 3

MSE, accuracy, and loss values for (LSTM) network

Metric	Value
MSE	0.019916
Accuracy	0.0592
Loss	0.0199

The Table 3 shows the MSE, accuracy, and loss values, highlighting the model's effectiveness in handling time-series data and predicting flow rates.

Gated recurrent unit (GRU) network. The GRU model's validation results are summarized in Table 4. The Table 4 includes MSE and loss values, providing insights into the model's performance in predicting flow rates with a simpler architecture compared to the LSTM.

Table 4

MSE and loss values for GRU network

Metric	Value
MSE	0.0828
Loss	0.5297

Generalized plot of neural networks. Finally, Table 5 shows the MSE results for the generalized plot, which combines the predictions of all neural networks.

Table 5

MSE for generalized plot

Metric	Value
MSE	10.739

This Table 5 illustrates the overall accuracy achieved by averaging the outputs of the individual models.

6. Discussion of received predicted minimum flow rate for hole cleaning

The findings from this study indicate that the developed neural network models, particularly the long short-term memory (LSTM) and gated recurrent unit (GRU) models, provide accurate predictions for the minimum flow rate necessary for efficient hole cleaning in drilling operations.

The LSTM model's superior performance, with a mean squared error (MSE) of 0.019169, can be attributed to its ability to retain information over extended periods, effectively capturing long-term dependencies in time-series data. This capability is critical for predicting drilling parameters that are influenced by historical data. The LSTM's effectiveness in understanding dynamic changes in drilling conditions over time allows for more precise predictions, making it particularly suitable for complex drilling scenarios (Table 3 and Fig. 10).

Similarly, the GRU model also demonstrates solid performance with an MSE of 0.0828. The GRU model balances accuracy and computational efficiency, thanks to its simpler architecture compared to LSTM. This simplicity results in faster training times and lower computational costs, making the GRU model well-suited for real-time applications where quick adjustments are necessary (Table 4 and Fig. 11). The difference in MSE values between the LSTM and GRU indicates that while both models are effective, the LSTM's more complex structure offers a slight edge in accuracy, particularly for datasets with more extensive temporal dependencies.

The neural network models developed in this study, including LSTM and GRU, offer significant improvements over traditional prediction models used in drilling operations. Traditional models often struggle with the non-linear relationships inherent in drilling data, whereas the advanced architectures of our neural network models are better equipped to capture these complexities. This capability leads to more accurate predictions across various drilling conditions, which is crucial for enhancing operational efficiency and minimizing risks, such as pipe sticking (Tables 3, 4).

Compared to existing models, our approach has several advantages. Firstly, the adaptability of neural networks allows for real-time data integration, enabling dynamic adjustments to drilling operations as conditions change. This contrasts with traditional static models that require manual recalibration and are less responsive to sudden changes in drilling conditions. Moreover, by incorporating machine learning techniques, our models continuously improve as more data becomes available, further enhancing their predictive accuracy and operational applicability.

The solutions developed in this study directly address the core problem identified in Section 2: the need for an accurate and reliable method to predict the optimal flow rate of drilling mud to enhance hole cleaning efficiency and prevent pipe sticking. By employing LSTM and GRU models, the study provides a robust solution that effectively captures the complex, non-linear relationships between drilling parameters and hole cleaning efficiency, offering significant improvements over traditional models (Fig. 10, 11). Additionally, by averaging the outputs of multiple models, a more accurate and reliable prediction was achieved, as this approach mitigates the errors that individual models might make at certain depths (Fig. 14).

The high predictive accuracy of these models allows for better planning and execution of drilling operations, reducing the likelihood of equipment failure and minimizing non-productive time. This demonstrates that the study has successfully filled a critical gap in the field, providing a valuable tool for drilling engineers.

While this study presents a promising approach to predicting drilling parameters, several limitations should be considered. One key limitation is the dependency on high-quality, comprehensive data for training the neural network models. The accuracy of these models is directly linked to the quality and diversity of the data available; thus, their effectiveness may diminish in environments where such data is scarce or incomplete. This suggests that the models are best suited for applications where robust data collection systems are in place, and continuous monitoring is feasible.

Another limitation is that the models were developed and tested primarily under specific geological conditions. Therefore, their generalizability to other regions with different geological characteristics may be limited without further calibration or retraining. While the models provide high accuracy within their training scope, significant adjustments may be required to maintain effectiveness in new environments.

Beyond the identified limitations, the study also has some shortcomings that could impact the practical application of its findings. One major shortcoming is that the models do not currently incorporate all potential variables that could affect drilling operations, such as unexpected geological anomalies or equipment malfunctions. The exclusion of these variables could lead to less accurate predictions in scenarios where such factors play a significant role. Additionally, the computational demands of running LSTM and GRU models, especially in real-time applications, may pose challenges in field settings with limited resources.

There is also a concern about the risk of overfitting to the specific training data. If the dataset used to train the models is not sufficiently diverse, the models may perform well on the training data but fail to generalize to new data. This overfitting could limit the models' practical utility, necessitating ongoing validation and tuning to maintain performance across different drilling operations.

Future research should focus on expanding the dataset to include a broader range of geological conditions and drilling scenarios, enhancing the models' generalizability and reducing the risk of overfitting. Additionally, incorporating more variables into the models, such as real-time equipment performance data and indicators of geological anomalies, could further improve their predictive capabilities.

Exploring alternative neural network architectures or developing hybrid models that combine machine learning techniques with traditional physics-based approaches could also enhance prediction accuracy and computational efficiency. Furthermore, research into optimizing these models for real-time applications, possibly through hardware accelerations like edge computing devices, could facilitate their practical deployment in diverse drilling environments.

The findings from this study indicate that the developed neural network models, particularly the Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) models, provide accurate predictions for the minimum flow rate necessary for efficient hole cleaning in drilling operations.

The LSTM model's superior performance, with a Mean Squared Error (MSE) of 0.019169, can be attributed to its ability to retain information over extended periods, effectively capturing long-term dependencies in time-series data. This capability is critical for predicting drilling parameters influenced by historical data. The LSTM's effectiveness in understanding dynamic changes in drilling conditions over time allows for more precise predictions, making it particularly suitable for complex drilling scenarios (Table 3 and Fig. 10). In contrast to traditional linear models like those used in previous studies [2], which often fail to capture these temporal dependencies, the LSTM model leverages its recurrent architecture to continuously update its predictions, resulting in more accurate and reliable outputs.

Similarly, the GRU model demonstrates solid performance with an MSE of 0.0828. This balance between accuracy and computational efficiency is crucial for real-time applications. The GRU model's simpler architecture allows for faster training times and lower computational costs, making it particularly suitable for real-time applications where quick adjustments are necessary (Table 4 and Fig. 11). When compared with Support Vector Machines (SVM) models, such as those discussed by [8] in the context of fiber sweeps for hole cleaning, the GRU model's adaptability to dynamic drilling conditions presents a significant advantage.

The neural network models developed in this study, including LSTM and GRU, offer significant improvements over traditional prediction models. Traditional approaches, such as those detailed by [3] for optimizing hole cleaning in horizontal wells, often struggle with the non-linear relationships inherent in drilling data. In contrast, the advanced architectures of our neural network models are better equipped to capture these complexities, leading to more accurate predictions across various drilling conditions. This capability is crucial for enhancing operational efficiency and minimizing risks, such as pipe sticking (Tables 3, 4).

Compared to existing SVM-based models, which require extensive data preprocessing and feature selection [8], our LSTM and GRU models handle sequential dependencies and real-time data integration with greater ease. These neural network models continuously improve as more data becomes available, further enhancing their predictive accuracy and operational applicability. This contrasts with static models, which are less responsive to sudden changes in drilling conditions and require manual recalibration, as noted by [4].

The solutions developed in this study directly address the core problem identified in Section 2: the need for an accurate and reliable method to predict the optimal flow rate of drilling mud to enhance hole cleaning efficiency and prevent pipe sticking. By employing LSTM and GRU models, the study provides a robust solution that effectively captures the complex, non-linear relationships between drilling parameters and hole cleaning efficiency, offering significant improvements over traditional models (Fig. 10, 11). Additionally, by averaging the outputs of multiple models, a more accurate and reliable prediction was achieved, as this approach mitigates the errors that individual models might make at certain depths (Fig. 14).

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Beyond the identified limitations, the study also has some shortcomings that could impact the practical application of its findings. One major shortcoming is that the models do not currently incorporate all potential variables that could affect drilling operations, such as unexpected geological anomalies or equipment malfunctions. The exclusion of these variables could lead to less accurate predictions in scenarios where such factors play a significant role. Additionally, the computational demands of running LSTM and GRU models, especially in real-time applications, may pose challenges in field settings with limited resources.

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Exploring alternative neural network architectures or developing hybrid models that combine machine learning techniques with traditional physics-based approaches could also enhance prediction accuracy and computational efficiency. Furthermore, research into optimizing these models for real-time applications, possibly through hardware accelerations like edge computing devices, could facilitate their practical deployment in diverse drilling environments.

During the development of various neural network models, one of the key challenges encountered was related to model training. At a certain point, the models reached a stage where further training did not significantly improve their performance, indicating that the results had plateaued. This highlights the critical importance of the quality of the data used for training. High-quality, comprehensive datasets are essential for achieving the best possible outcomes when developing neural networks for applications in the oil and gas industry.

To optimize the effectiveness of neural network models in drilling operations, it is advisable to use the largest and most accurate datasets available. Moreover, the model's universality can be significantly enhanced by incorporating data from diverse geographic locations, reflecting various geological conditions. This approach ensures that the model is exposed to a wide range of scenarios, improving its ability to generalize and perform accurately in different settings. Since the geology can vary greatly across different regions, collecting data from multiple parts of the world is crucial for developing a robust and reliable model.

Once a neural network model, or a set of models, is successfully developed-as demonstrated in this study – it can be implemented either as standalone software or integrated into existing systems. However, this process requires the expertise of a software development team or software engineers to ensure that the implementation is smooth and effective. It's important to note that, as this study did not extend into the implementation phase, the recommendations provided here are based on theoretical understanding and may need further validation during practical deployment.

To enhance overall drilling efficiency, it is recommended to integrate the neural network model into existing monitoring and control systems. This integration will enable real-time adjustments to drilling fluid parameters, optimizing the hole cleaning process. By continuously monitoring and predicting the optimal flow rates, drilling operations can achieve higher efficiency, reduce non-productive time, and lower operational costs. The implementation of this model provides a proactive approach to managing drilling challenges, ensuring smoother operations and improved productivity. Also, it is worth mention that these models can be retrained with better dataset and for given field, thus increasing the accuracy.

In conclusion, the neural network model developed in this study offers a significant advancement in predicting the optimal minimum flow rate for effective hole cleaning. Its validated accuracy and practical recommendations for implementation make it a valuable tool for enhancing drilling operations and achieving better overall efficiency.

7. Conclusions

1. The neural network model developed in this study effectively predicts the minimum flow rate required for efficient hole cleaning. By leveraging advanced architectures such as long short-term memory (LSTM) and gated recurrent unit (GRU), the model accurately captures the complex, nonlinear relationships between various drilling parameters and the efficiency of hole cleaning. The results demonstrate that the model can handle time-series data, making it suitable for real-time applications in dynamic drilling environments.

2. The model's accuracy and reliability were validated using real-world field data. The mean square error (MSE) values obtained-0.019169 for LSTM and 0.0828 for GRU-indicate high predictive accuracy. The validation process confirmed that the model could reliably predict the necessary flow rates under different drilling conditions, thereby minimizing the risk of stuck pipes and associated downtime. The robust performance across varied datasets highlights the model's potential for broader application in the industry.

Conflicts of interest

The authors declare that they have no conflicts of interest in relation to the current study, including financial, personal, authorship, or any other, that could affect the study and the results reported in this paper.

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Data availability

Data will be made available on reasonable request.

Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the current work.

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