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Mechanism and Intelligence Coupled Pump Pressure Prediction and Application for Downhole Sand Plugging#

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ABSTRACT

Efficient development of shale oil and gas in China relies on factory operations and large-scale fracturing technology. Large-scale fracturing of shale oil and gas requires a long time and numerous equipment and facilities, with frequent and severe incidents of fracturing sand blockage. The research on early warning research in these incidents is crucial for the safety of shale oil and gas fracturing operations. However, the effective methods for analyzing the main control factors of fracturing sand blockage and predicting the pump pressure during operations are lacked. To study this issue, considering the fracturing mechanism and pump pressure variation characteristics, a method for real-time prediction of pump pressure during fracturing operations has been established to conduct sand blockage early warning research here. First, a fracturing simulator was used to simulate the entire process of pump pressure changes during fracturing. By altering different fluid properties and formation parameters, the main control factors of pump pressure variation were analyzed, and the grey correlation analysis method was used to rank these factors. Secondly, based on fracture mechanics, proppant transport theory, and the Long Short-Term Memory (LSTM) neural network model, a framework and model for predicting pump pressure during operations was established, forming a method for early warning of fracturing sand blockage under the integration of mechanism and intelligence. Finally, the early warning method for sand blockage was applied to actual field fracturing operations. Results indicate that the factors affecting the pump pressure of a typical well, from most to least significant, are discharge rate, fluid viscosity, differential principal stress, sand concentration, number of fracture clusters, and number of perforations. When other parameters remain constant, as fluid viscosity, differential principal stress, and discharge rate increase, the pump pressure increases; as the number of fracture clusters, perforations, and sand concentration increase, the pump pressure decreases. This method can be used for the identification and early warning of fracturing sand blockage incidents in the actual field operations, which is 19 seconds earlier than on-site manual identification, with a relative error of about 6.8%. The predicted pump pressure is friendly matched with the actual field one, which is helpful in accurate early warning of fracturing sand blockage.

Keywords: shale reservoir, sand plugging, fracture mechanics, intelligent early-warning, LSTM

NONMENCLATURE

Abbreviations	
LSTM	Long Short-Term Memory
RNN	Recurrent Neural Network
MSE	Mean Square Error
MAE	Mean Absolute Error
RE	Relative Error
Symbols	
$\xi_{i,k}$	Correlation coefficient
ρ	Resolution coefficient
γ_i	Grey relational degree
m	Factor count
f_t	Forget gate
i_t	Input gate
$\tilde{C}_t$	Cell status
h_t	Hidden layer
$\sigma(x)$	Activation functions

1. INTRODUCTION

The efficient development of shale oil and gas heavily relies on factory-mode operations and large-scale fracturing technologies. Compared to conventional fracturing, large-scale shale fracturing involves longer operation times, more equipment, and more complex

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on-site conditions. Among the potential risks, sand plugging incidents occur most frequently and often lead to severe consequences. In minor cases, sand plugging can damage equipment and pipelines; in more serious scenarios, they may impair formation permeability, cause environmental contamination, or even lead to well abandonment. Therefore, developing safety early-warning methods for sand plugging during shale fracturing operations is of great significance for ensuring process safety[1-3].

Field experience demonstrates that a sharp increase in pump pressure observed on fracturing operation curves serves as a critical indicator of sand plugging incidents. Based on this, researchers have developed various sand plugging identification methods, primarily including characteristic analysis, net pressure matching, slope reversal, and data-driven approaches. Huang[4] established a characteristic analysis method through extensive study of field fracturing curves, providing a theoretical foundation for sand plugging identification based on pressure trend analysis. Liang[5] utilized the slope of net pressure-time log-log curves, where a slope exceeding 1 indicates downhole sand plugging. Yu[6] implemented real-time sand plugging warnings by monitoring fracturing parameters and analyzing pressure-time log-log curve slopes. To improve prediction accuracy, Hu[7] employed Long Short-Term Memory (LSTM) neural networks, achieving more accurate forecasting of fracturing curve trends. While most conventional methods rely heavily on operator experience—increasing risks of misjudgment and missed detection—data-driven approaches offer greater objectivity. However, they predominantly depend on statistical patterns without adequately incorporating the mechanistic characteristics of the fracturing process[8-11].

Therefore, this study develops an intelligent warning model integrating mechanical analysis with data-driven approaches. The methodology combines fracture mechanics simulations with LSTM modeling to identify dominant pressure-influencing factors and establish a physics-informed warning system, validated through field case studies.

2. MATERIAL AND METHODS

2.1 Fracturing simulation

To establish an intelligent early warning method for sand plugging that integrates mechanistic modeling with data-driven approaches, it is essential first to analyze the underlying relationships between fracturing operational parameters and the corresponding treatment curves. The ZFRAC simulator, developed by Olson and Wu[12], can be employed to solve fracture extension problems, with its specific computational workflow illustrated in Figure 1.

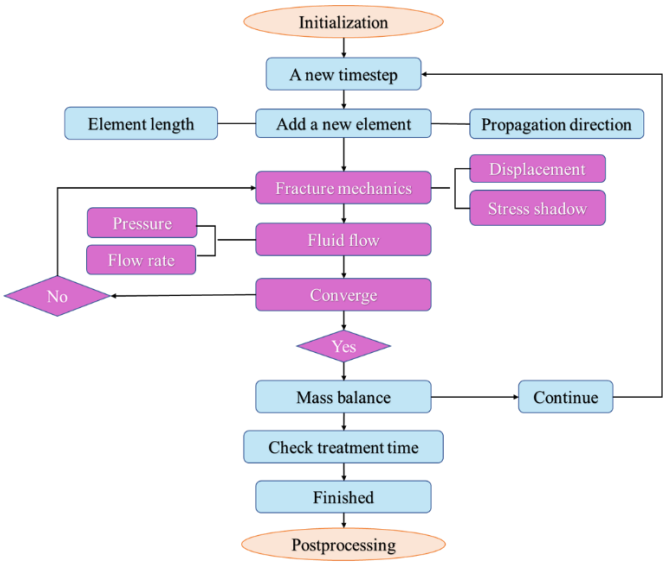


Fig. 1 Flowchart of numerical solution for fracturing treatments [12]

2.2 Sensitivity analysis

Based on the principles of fracture mechanics and horizontal wellbore flow equations, six parameters—including discharge rate, proppant concentration, fluid viscosity, principal stress difference, number of perforations, and number of fracture clusters—were selected as independent variables to investigate the dominant factors influencing pump pressure variation during the fracturing process.

Establishing a numerical model based on the formation and well location data of a shale oil well..Five discrete flow rate stages were established to analyze the impact of flow rate variation on the characteristics of the pump pressure curve. As shown in Figure 2(a), the pump pressure increases progressively with each step-wise increase in flow rate, indicating a positive correlation between higher flow rates and elevated pump pressure.

Similarly, while keeping other variables constant, corresponding pump pressure curves were generated by individually varying proppant concentration, fluid viscosity, principal stress difference, number of perforations (two clusters), and number of fracture clusters, as presented in Figures 2(b) to 2(f).

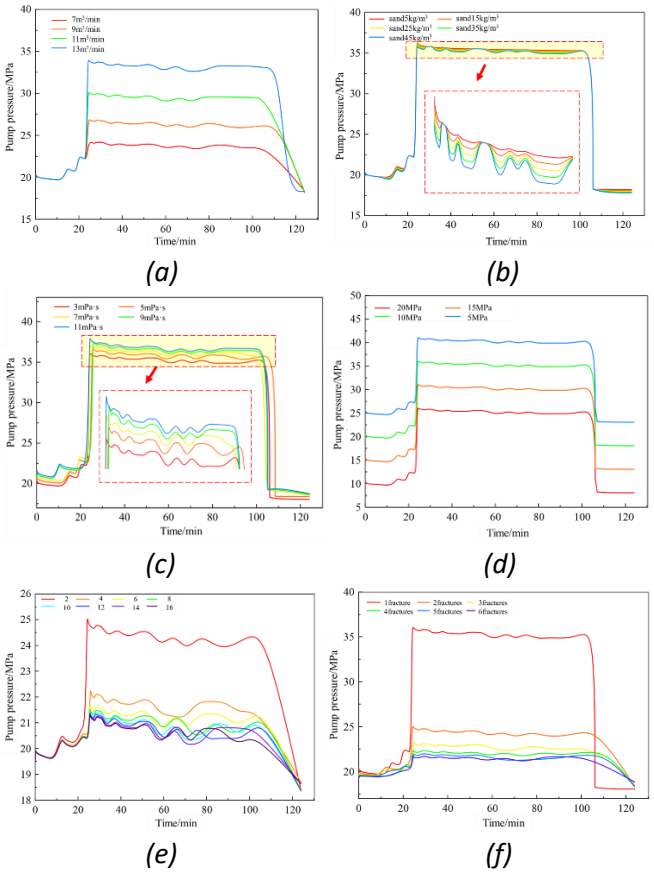


Fig. 2 The effect of changing various control factors displacement on pump pressure curve

2.3 Analysis of main controlling factors

Based on the aforementioned simulation results of fracturing mechanisms, grey relational analysis was employed to identify the dominant factors influencing pump pressure behavior. A higher grey relational degree indicates a stronger correlation between factors, while a lower value suggests weaker association[13]. For screening these dominant factors, data sequences were normalized using the initial value method to render them dimensionless. The displacement difference was applied to evaluate the proximity between sequences in terms of developmental trends or magnitude scales. The correlation coefficient between pump pressure and any comparative sequence at a given sample point is calculated as follows:

$$\xi_{i,k} = \frac{\min_i \min_k |x_0(k) - x_i(k)| + \rho \max_i \max_k |x_0(k) - x_i(k)|}{|x_0(k) - x_i(k)| + \rho \max_i \max_k |x_0(k) - x_i(k)|} i, k = 1,2,\ldots,m \quad (1)$$

$$x_{i,k} = \frac{\widetilde{x_{i,k}} - \mu}{\sigma} \quad (2)$$

$$\gamma_i = \frac{1}{m} \sum_{i=1}^{m} \xi_{i,k} \quad (3)$$

Where $\xi_{i,k}$ is the correlation coefficient; ρ is the resolution coefficient; $\widetilde{x_i}$ is the dimensionless data; μ and σ are the mean and standard deviation of the sample data. Equation (2) defines the standardization process. The terms *min* and *max* denote the global minimum and maximum of the sample data, respectively; γ_i is the grey relational degree, and m is the factor count.

Table 1. Gray correlation degree ranking table

Ranking	*Parameter*	*Grey Relational Grade*
1	*displacement*	*0.858*
2	*fluid viscosity*	*0.853*
3	*differential stress*	*0.834*
4	*sand concentration*	*0.767*
5	*number of fracture clusters*	*0.749*
6	*number of perforations*	*0.719*

3. THEORY AND CALCULATION

3.1 Model framework construction

In shale oil and gas fracturing, pump pressure variations serve as a critical indicator for detecting screen-outs. The Long Short-Term Memory (LSTM) network—an enhanced recurrent neural architecture—is well-suited for time-series forecasting due to its gated memory cells and temporal modeling capability. A standard LSTM consists of three gating mechanisms (forget, input, and output gates) that regulate information flow. Its structure is shown in Figure 3.The activation functions for the three gates and the tanh operation are defined as follows. Beyond the LSTM layer, a linear layer is added to transform outputs into predicted pump pressure, as given in Equation 9.

$$f_t = \sigma(W_f \cdot [X_t, h_{t-1}] + b_f) \quad (4)$$

$$i_t = \sigma(W_i \cdot [X_t, h_{t-1}] + b_i) \quad (5)$$

$$\tilde{C}_t = tanh(W_C \cdot [X_t, h_{t-1}] + b_C) \quad (6)$$

$$\sigma(x) = \frac{1}{1+e^{-x}} \quad (7)$$

$$tanh(x) = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}} \quad (8)$$

$$y = W \cdot x + b \quad (9)$$

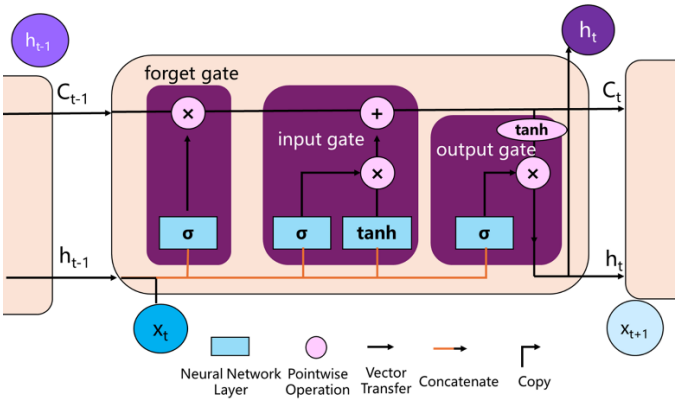


Fig. 3 Schematic diagram of long short-term memory neural network structure

Based on key pump pressure influencing factors, a predictive model was developed for fracturing operations. Input parameters underwent dimensionality reduction to enhance accuracy. Given the relative stability of in-situ stress fields, fracture clusters, and perforations during operations, the model uses pump pressure, flow rate, fluid viscosity, and proppant concentration to forecast pressure in subsequent intervals.

The LSTM network was trained on second-by-second pressure data using a sliding window approach: seven historical values predict the eighth step, with predictions iteratively fed forward for continuous forecasting. This rolling mechanism enables proactive screen-out prevention.

The architecture comprises input, LSTM, fully connected layers, and output layers, optimized with MSE loss and Adam algorithm. Training utilized early proppant-stage data to predict later performance. After evaluating network complexity and error tolerance, an 8-node hidden layer configuration was adopted (Figure 4).

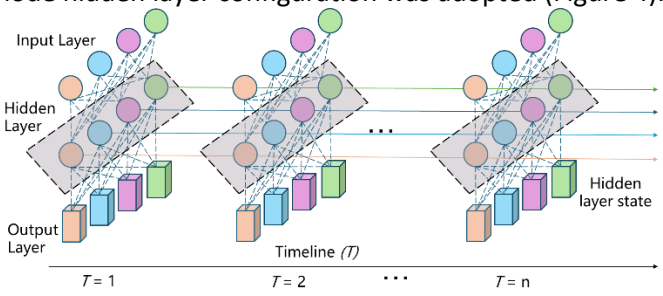


Fig. 4 LSTM model structure diagram

As shown in Figure 5, the LSTM model's rolling predictions demonstrate strong alignment with simulated pressure data, indicating excellent fitting performance. The model thus provides reliable real-time forecasting of future pump pressure trends, establishing a robust foundation for operational decision-making.

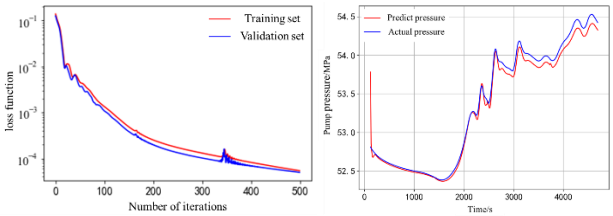


Fig. 5 Loss function and rolling prediction effect of pump pressure

3.2 Warning method

Distinct pump pressure patterns reflect different fracturing processes. A sudden pressure surge with a slope exceeding 1, occurring under stable flow rate conditions, indicates near-wellbore screen-out.

As illustrated in Figure 6, an intelligent screen-out warning workflow was established accordingly. Real-time fracturing data are first collected and preprocessed for LSTM model training. The model generates predicted pressure curves, from which real-time pressure slopes (first derivatives) are calculated. A screen-out incident is identified when the slope exceeds 1 while both flow rate and proppant concentration remain stable.

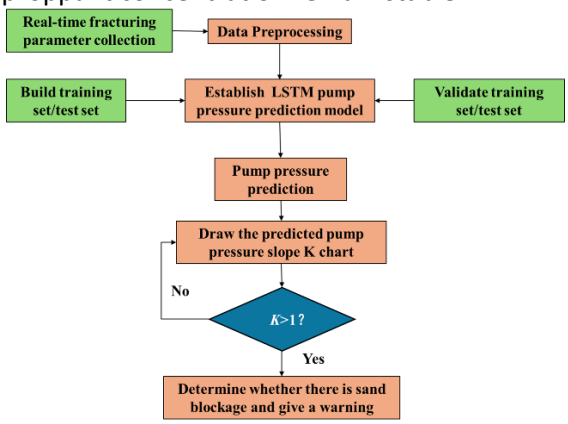


Fig. 6 Intelligent warning process for sand blockage

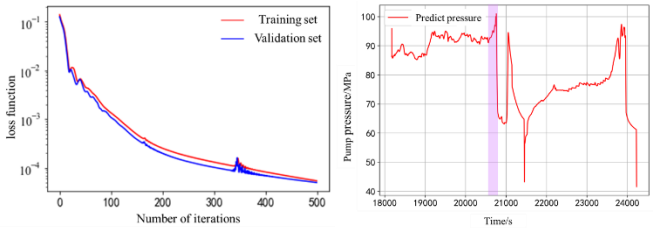
4. RESULTS

For this study, operational data from the first five hours (out of a total 7.1 hours) of a fracturing operation in a shale oil well were selected, including pump pressure, flow rate, and proppant concentration. The subject horizontal well has a lateral length of 1,077.4 meters and was fractured in 20 stages across 97 clusters, with a pumping rate maintained between 14–16 m^3/min. Key well parameters are provided in Table 2.The established intelligent sand plugging warning procedure was applied to this dataset to forecast pump pressure trends and provide early sand plugging detection.

Table 2. Summary table of basic parameters for example well

Number	Top layer depth(m)	Bottom layer depth(m)	Length(m)
1	3478.5	3506.5	28.0
2	3506.5	3563.0	56.5
3	3563.0	3753.5	190.5
4	3753.5	3946.0	192.5
5	3946.0	4120.0	174.0
6	4120.0	4450.5	330.5
7	4450.5	4650.0	199.5

The first five hours of fracturing data from this shale oil well were used to develop a pump pressure prediction model, with this dataset serving as the training set for the LSTM network. The input sequence for prediction consisted of pump pressure values paired with their corresponding fracturing timestamps. A schematic of the model's loss function during training is shown in Figure 7-a.The predicted pump pressure data for the well are presented in Figure 7-b, while the corresponding slope variation of the predicted pressure is illustrated in Figure 8. Key model evaluation metrics are summarized in Table 3.



(a) *(b)*

Fig. 7 Schematic diagram of model loss function and predicted pump pressure and slope

Table 3. Model evaluation parameters

Dataset	MSE	MAE	RE（%）
training set	37.60	3.78	5.52
test set	43.73	4.87	6.81

Validation results indicate a mean squared error (MSE) of 43.73, a mean absolute error (MAE) of 4.87, and a relative error (RE) of approximately 6.81% on the test set. Comparison between the predicted and actual pressure curves shows strong agreement, demonstrating that the model accurately captures the underlying trends in pump pressure behavior.

Based on the predicted pump pressure curve, a plot of its slope variation was generated. A sand plugging incident is identified when the slope exceeds a value of 1. As shown in Figure 8, a sand plugging occurred at approximately 20,730 seconds.

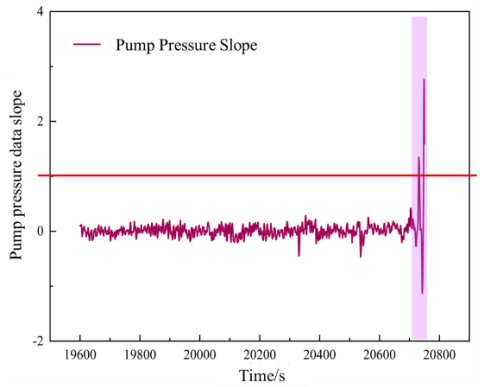


Fig. 8 Diagram of the slope change for predicted pump pressure

5. DISCUSSION

The field fracturing curve shown in Figure 9 illustrates various operational responses during the process:

(1) Sand plugging occurrence: A sharp pump pressure surge at 20,749 seconds indicated an intra-formational sand plugging. Proppant addition was immediately halted (proppant concentration dropped to zero) and displacement fluid was pumped—equivalent to approximately 1–2 wellbore volumes—at a stable rate before gradual shutdown to prevent wellbore sand-up. Following this, the pump pressure dropped rapidly and stabilized at its minimum value, representing the shut-in pressure.

(2) Sand plugging confirmation: A subsequent injection test, involving a small volume of fluid, resulted in a rapid pressure increase, confirming the downhole sand plugging.

(3) Mitigation measures: To address the sand plugging, the well was opened for flowback, reducing treatment pressure to zero. Field data indicated low proppant concentration and continuous pressure fluctuations prior to sand plugging, suggesting poor formation acceptance—possibly due to mismatched proppant size. Switching to smaller-sized proppant may improve compatibility.

The predicted pump pressure aligns closely with field measurements, demonstrating accurate sand plugging early warning. The proposed method proves effective in identifying and alerting sand plugging incidents, offering practical value for fracturing operations.

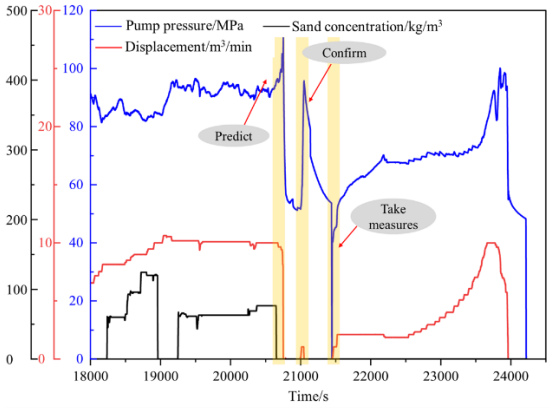


Fig. 9 Fracturing construction curve for a certain section of a shale oil well (last 2 hours)

6. CONCLUSIONS

This study utilized the ZFRAC simulator to investigate fracture propagation during hydraulic fracturing, analyzing fracture opening, shear behavior, stress shadow effects, and operational pump pressure. Key factors influencing pump pressure trends were examined through sensitivity analysis, with Grey Relational Analysis employed to quantify parameter correlations.

An intelligent sand plugging warning methodology integrating mechanistic and data-driven approaches was developed. Using pump pressure, flow rate, fluid viscosity, and proppant concentration as input parameters for the LSTM prediction model, the system forecasts future pump pressure with a relative error of 6.8%, demonstrating strong reliability.

Field application of this sand plugging prediction method successfully issued an early warning at approximately 20,730 seconds in the case study well. Operational data confirmed a sharp pressure increase at 20,749 seconds, indicating intra-formational sand plugging. Subsequent pressure spikes during minor fluid injection validated the incident. The model provided a 19-second advance warning compared to manual field detection. Predicted pressures showed close alignment with actual field measurements, enabling accurate sand plugging alerts and offering valuable insights for shale oil and gas fracturing operations.

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