International Journal of Petroleum Technology, 2025, 75-86

Published by Avanti Publishers

International Journal of Petroleum Technology

ISSN (online): 2409-787X

Development of an ANN-Driven Empirical Equation for Real-Time Prediction of Natural Gas Flow through Surface Well Chokes

Ashraf Ahmed[1], Ahmed A. Mahmoud[1,2], Murtada A. Elhaj[3,*] and Salaheldin Elkatatny[1]

[1]*College of Petroleum Engineering & Geosciences, King Fahd University of Petroleum & Minerals, Dhahran 31261, Saudi Arabia*
[2]*Center for Integrative Petroleum Research, King Fahd University of Petroleum & Minerals, Dhahran 31261, Saudi Arabia*
[3]*Process Engineering Department, Memorial University of Newfoundland, St. John's, NL A1C 5S7, Canada*

ARTICLE INFO

Article Type: Research Article

Academic Editor: Shenglai Guo

Keywords:
Flow control
Surface choke
Natural gas flow
Artificial neural networks

Timeline:
Received: September 03, 2025
Accepted: November 04, 2025
Published: November 18, 2025

Citation: Ahmed A, Mahmoud AA, Elhaj MA, Elkatatny S. Development of an ANN-driven empirical equation for real-time prediction of natural gas flow through surface well chokes. Int J Pet Technol. 2025; 12: 75-86.

DOI: https://doi.org/10.15377/2409-787X.2025.12.5

ABSTRACT

To maximize production efficiency, natural gas flow via surface well chokes must be optimized. The nonlinear character of this flow frequently causes problems for conventional empirical correlations and mechanistic models. To accurately forecast gas flow rates using field data, this study develops an Artificial Neural Network (ANN) model that considers temperature, gas gravity, choke size, and pressures. The main innovation is that the optimized network is used to derive an exact, closed-form empirical equation, going beyond the typical "black-box" use of ANN. This equation enables the estimation of flow rate in real-time without requiring the execution of the ANN model, providing engineers with a valuable tool at present. The 5-neuron optimized ANN demonstrated remarkable accuracy, with training and testing average absolute percentage errors (AAPE) below 2% and a correlation coefficient (R) over 0.99. When tested on unknown data, the resultant equation performed well (R=0.999, AAPE=2.78%), outperforming conventional techniques in terms of generalization and predictive power. By connecting data-driven analytics with field operational realities for well management, this research represents a significant leap forward.

*Corresponding Author
Email: aelhaj@mun.ca
Tel: +1 (709) 864 8813

1. Introduction

Optimizing natural gas flow through surface well chokes is essential for maximizing efficiency in the oil and gas industry. Properly managing this flow is crucial, as it directly affects production rates, reservoir health, and economic profitability. Effective choke optimization ensures that natural gas is produced at optimal rates, preventing issues such as excessive pressure drops or flow restrictions that can lead to reduced output or damage to the reservoir. As natural gas remains a key component of the global energy supply, refining these processes is increasingly important to boost production, lower operational costs, and maintain competitive advantages in a dynamic energy market [1-3].

Surface well chokes are mechanical devices installed at the well's surface to regulate the flow of natural gas from the well to processing facilities. They are engineered to control the pressure drop across the choke, which directly influences the gas flow rate. The main purpose of these chokes is to manage the well's output, ensuring that the production rate aligns with reservoir management strategies while preventing excessive drawdown that could potentially damage the reservoir. Furthermore, surface well chokes are essential in minimizing the risk of hydrate formation and controlling erosion in downstream equipment [1, 4-7].

The performance of a choke is impacted by several factors, including reservoir pressure, choke size, gas composition, and wellhead temperature. The dynamic interplay of these variables creates substantial challenges in maintaining optimal control. Consequently, optimizing gas flow through surface well chokes is a complex task that demands advanced modeling and analysis. While traditional methods can be somewhat effective, they frequently struggle to account for the dynamic and multifaceted nature of the factors that affect flow rates [2, 5, 7-11].

Traditionally, optimizing natural gas flow through well chokes has depended on empirical correlations and mechanistic models. These approaches are based on the principles of fluid dynamics and thermodynamics, providing a theoretical foundation for predicting flow behavior. Empirical correlations, in particular, have been widely employed to estimate flow rates by considering factors such as choke size, upstream pressure, and gas properties. Derived from field data, these correlations are relatively easy to use. However, their accuracy is often limited, particularly when applied to highly variable conditions or unconventional gas reservoirs, where they may not fully capture the complexity of the flow dynamics [12-14].

Mechanistic models, in contrast, aim to replicate the physical processes taking place within the wellbore and choke. These models consider elements such as multiphase flow, phase behavior, and pressure-temperature effects. Although they offer more detailed insights compared to empirical correlations, mechanistic models are computationally demanding and require a significant amount of input data, which may not always be easily accessible. Additionally, these models often rely on simplifications and assumptions that can lead to inaccuracies, especially in more complex scenarios [15, 16].

The limitations of traditional methods highlight the need for advanced optimization techniques that can better capture the complexities of gas flow through well chokes. With the advent of digital technologies and the increasing availability of high-resolution data, there is an opportunity to leverage data-driven approaches to enhance flow optimization [17-19]. Among these approaches, artificial neural networks (ANNs) have gained significant attention due to their ability to model complex, nonlinear relationships without the need for explicit physical equations [20-23].

ANNs are computational models inspired by the human brain's structure and function. They comprise interconnected layers of artificial neurons, where each neuron processes input data and passes the output to the next layer. ANNs excel in tasks like pattern recognition, prediction, and classification. In natural gas flow optimization, ANNs can be trained on historical data to understand the relationships between input variables (e.g., choke size, pressure, temperature) and output variables (e.g., flow rate). Once trained, ANNs can predict optimal choke settings for different operating conditions, often offering greater accuracy and adaptability compared to traditional methods [24-27].

ANNs have found wide-ranging applications in the petroleum industry, revolutionizing various aspects of exploration, drilling, production, and reservoir management. In exploration, ANNs are used for seismic data interpretation, enhancing the accuracy of subsurface mapping and reducing the risk of drilling non-productive wells [28-30]. During drilling, ANNs could be applied for drilling optimization and minimization of non-productive time [31-34]. They are also employed in reservoir characterization, where ANNs help model complex reservoir properties and predict fluid behaviors under different conditions [35-41]. During production, ANNs assist in optimizing processes such as well performance analysis, predicting equipment failures, and improving enhanced oil recovery (EOR) techniques [42-46]. By handling vast amounts of data and uncovering patterns that traditional methods may overlook, ANNs contribute to more efficient and cost-effective operations across the petroleum industry.

Using ANNs to optimize natural gas flow through surface well chokes provides several benefits. ANNs excel at capturing nonlinear relationships and complex interactions between variables, leading to more accurate flow rate predictions and improved decision-making. They can also process vast amounts of data, uncovering patterns that traditional models might miss, which enhances optimization strategies. Additionally, ANNs are adaptable and can be retrained with new data, making them ideal for dynamic environments where conditions frequently change. These capabilities make ANNs a powerful tool for optimizing natural gas production in varying operational contexts [47-49].

ANN, hybrid learning, and ensemble machine-learning frameworks have been used in several recent research to forecast choke flow and production rate [50-52]. These studies validate that data-driven models outperform traditional empirical correlations in terms of predictive accuracy, but they also highlight enduring drawbacks, such as limited dataset scope, limited cross-field transferability, limited interpretability of ANN architectures, and minimal validated deployment in real-world production systems. The current study's aim on creating a reliable, field-deployable ANN-based correlation for choke flow prediction is motivated by these deficiencies.

This paper focuses on developing an ANNs model to accurately predict gas flow rates through surface well chokes, considering key variables such as pressure, temperature, choke size, and gas specific gravity. By leveraging the optimized ANN model, an empirical equation will be derived to streamline the prediction process, enabling more accurate and efficient gas flow rate estimations. This approach aims to enhance decision-making in well management and optimize production efficiency.

2. Methodology

In this study, more than 150 data points were gathered from a gas field in Sudan to create an artificial intelligence model that accurately reflects field production data. The dataset included key variables such as choke size (D_{ch}), tubing temperature (T), upstream and downstream tubing pressures (P_{up} and P_d), gas specific gravity (γ), and gas flow rates (Q). These inputs, selected based on empirical correlations and gas law principles, were used to predict gas flow rates effectively.

Before applying the AI technique, the obtained dataset was thoroughly evaluated and processed to ensure its quality and representation. The statistics feature analysis for the data points included identifying the minimum, maximum, median, and mean values, as well as distribution factors including kurtosis, skewness, and standard deviation. These statistics are essential for machine learning practitioners to ensure that the input data aligns with the expected ranges. The analysis demonstrated that this data set encompassed a wide range and provided a comprehensive representation of data distribution, as summarized in Table **1**.

Additionally, the correlation coefficients and the intensity of the linear correlations between each variable and the gas flow rate were used to assess the importance of each, as shown in Fig. (**1**). High correlation values for choke size and pressures indicated their significant impact on predicting gas flow rates. The lower correlation coefficients for tubing temperature and gas specific gravity indicated an absence of a linear relationship; however, they could not be excluded as the variations in these parameters still significantly affected the gas flow rate, as illustrated in the cross-plots in Fig. (**2**). Consequently, all variables were included as model inputs.

Table 1: Dataset statistics.

Parameter	D_{ch} 1/64"	T °R	P_{up} psig	P_d psig	ɣ	Q mmscf/d
Minimum	16.00	535.20	520.00	100.00	0.59	2.17
Maximum	128.00	564.00	1840.00	500.00	0.63	17.17
Median	32.00	553.20	1570.00	200.00	0.59	7.64
Mean	49.72	552.12	1322.18	274.30	0.59	8.93
Kurtosis	3.57	3.91	1.98	2.04	15.18	2.21
Skewness	1.39	-0.26	-0.69	0.48	3.48	0.40
Standard Deviation	36.05	5.24	442.71	130.41	0.01	4.56

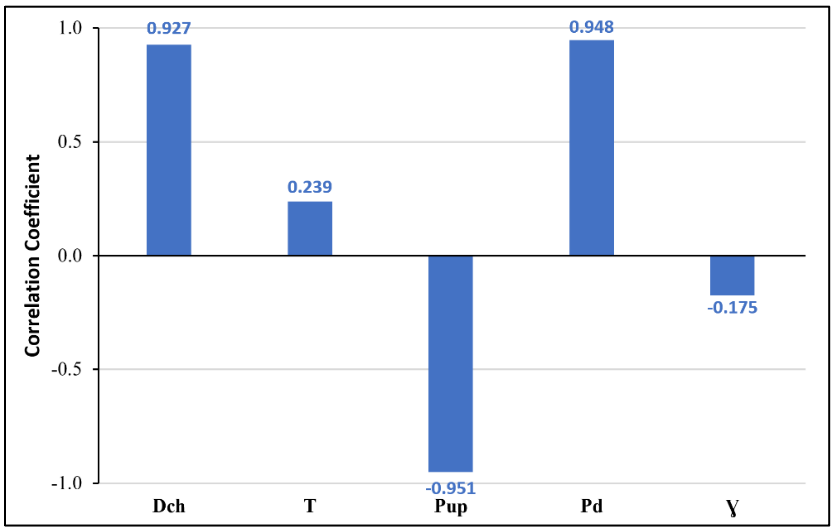

Figure 1: The correlation coefficient of the parameters with flow rates.

To ensure the quality and reliability of the dataset, it was meticulously cleaned and filtered based on statistical descriptions to remove erroneous and unrealistic data, including negative values, zeros, NaNs, and missing entries. These preprocessing steps were essential to prepare the data for model development.

To estimate the gas flow rate (Q), the ANN model was created with five neurons in the input layer, one hidden layer, and one neuron in the output layer. Sensitivity analysis was used to identify the ideal number of neurons in the buried layer.

The filtered dataset was randomly divided, allocating 70% for training the model, 20% for testing, and the remaining 10% kept unseen by the algorithm for final validation. The ANN technique was then implemented using MATLAB, with extensive sensitivity and tuning analyses conducted to determine the optimal hyperparameters and functions. The optimality of the model was measured through some performance metrics, including the correlation coefficient (R), root mean square error (RMSE), average absolute percentage error (AAPE), and graphical analysis. The most desirable models exhibited the highest R values and the lowest RMSE and AAPE values. Each trial's performance and accuracy were rigorously evaluated using these criteria to determine the best model. In addition to creating an optimized model, the ultimate goal was to transform the ANN black-box model into a transparent and interpretable white-box model in order to establish a new empirical correlation. Therefore, a new correlation was developed from the best-performing model, and it was then validated with the reserved data points to ensure its accuracy and reliability. The procedures that followed for building the ANN model were presented in Fig. (**3**).

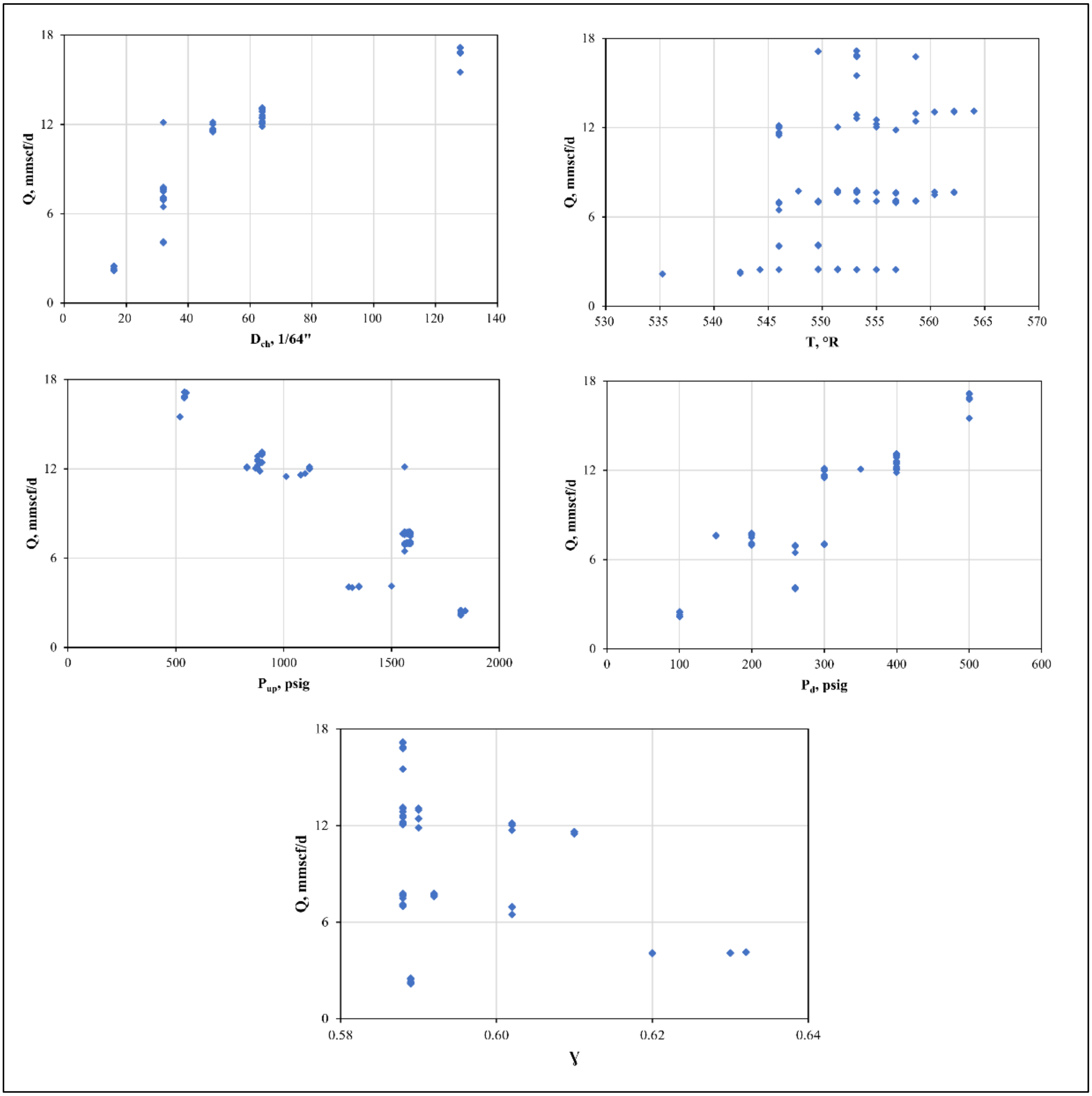

Figure 2: Cross plots between flow rates and the other parameters.

3. Results and Discussion

Artificial Neural Network (ANN) are computational systems modeled after the human brain's architecture, consisting of interconnected neurons that mimic the brain's information processing system. ANNs aim to solve complex problems by learning from examples, adapting to changes in the environment through learning rules, and utilizing various activation functions to determine outputs. These networks have evolved from basic models like the McCulloch–Pitts neuron to more advanced deep learning models, overcoming challenges like the selectivity-invariance problem. ANNs store information in a distributed manner, allowing parallel extraction of multiple pieces of information, similar to the human brain's powerful parallel processing capabilities.

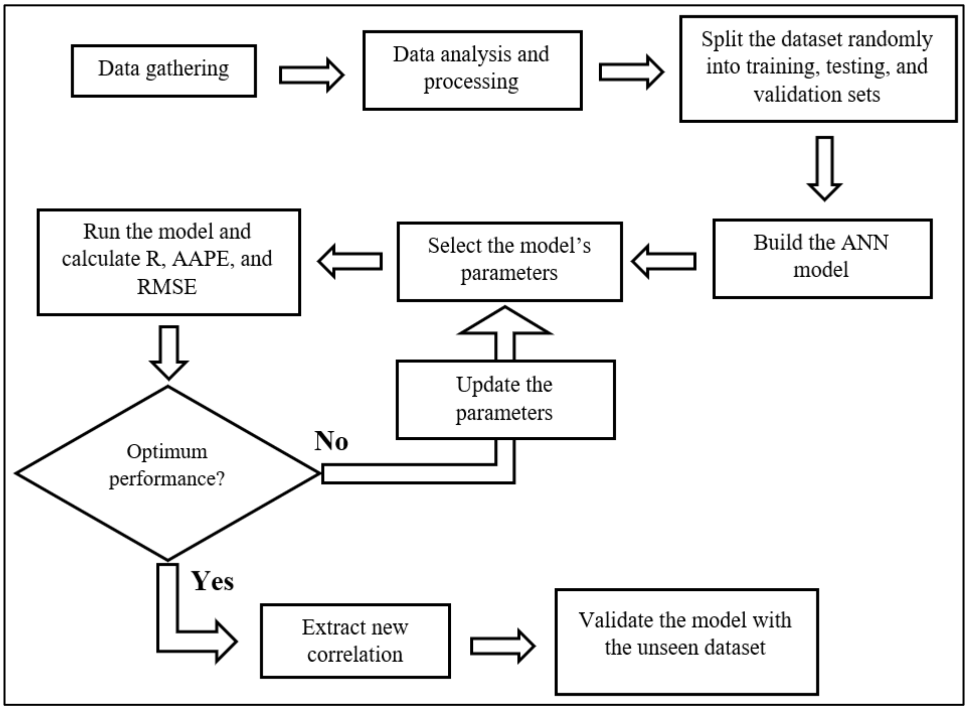

Figure 3: Model's development processes.

The ANN model emulates biological neural networks by using interconnected neurons with predetermined weights and biases. It is composed of three levels: input, hidden, and output. The parameters are received by the input layer, the hidden division processes them, and the output portion delivers the final result. These layers are connected through transfer functions and trained using various training algorithms. The best weights and biases in this system are found using the back-propagation technique. By experimenting with various scenarios for total neurons count, network functions, training algorithms, and transfer functions and applying the iteration approach, the optimum hyperparameters for model performance were recognized and validated to ensure accurate predictions.

The statistical relationships between the input parameters and the gas flow rate, illustrated in Fig. (**1**) and (**2**), provide critical insight into the model's inputs. Fig. (**1**) confirms the strong linear correlation of choke size and both upstream and downstream pressures with the flow rate, justifying their paramount importance. Conversely, Fig. (**2**) reveals the weak linear but significant non-linear relationships for tubing temperature and gas specific gravity. The scattering of data points in these cross-plots demonstrates that these variables influence the flow rate in complex ways that linear models cannot capture, underscoring the value of the ANN's ability to model such non-linear interactions and validating our decision to retain them as essential inputs.

The parameter tuning process identified the optimal model configuration, detailed in Table **2**, which includes 5 neurons in a single hidden layer. Sensitivity analyses, as described in the methodology, demonstrated that this optimized ANN-based model achieved high accuracy, with R value of +0.99, AAPE of 1.69% and 1.85%, and RMSE of 0.19 and 0.31 for training and testing, respectively. The cross-plots of actual versus predicted gas flow rates, shown in Fig. (**4**), further confirmed the model's excellent fitting accuracy.

Our systematic sensitivity analysis revealed that a single hidden layer with five neurons was sufficient to capture the complex, non-linear relationships in our dataset, as evidenced by the model's exceptional performance ($R > 0.99$, AAPE $< 2\%$ on test data). More complex architectures (e.g., additional hidden layers) showed no significant improvement in predictive accuracy on the testing set and introduced a risk of overfitting. A single-layer architecture resulted in a more compact and manageable final empirical correlation (Eq. 10), enhancing its transparency and utility for field engineers without sacrificing predictive power. This approach ensures the model is not only accurate but also optimally suited for its intended practical application.

Table 2: The ANN hyperparameters for the best performance model.

Parameter	Value
Number of neurons	5
Number of hidden layers	1
Training algorithm	Trainbr: Bayesian regularization backpropagation
Network function	Fitnet: Regression fitting
Transfer function	Tansig: Hyperbolic tangent sigmoid
Learning rate	0.12

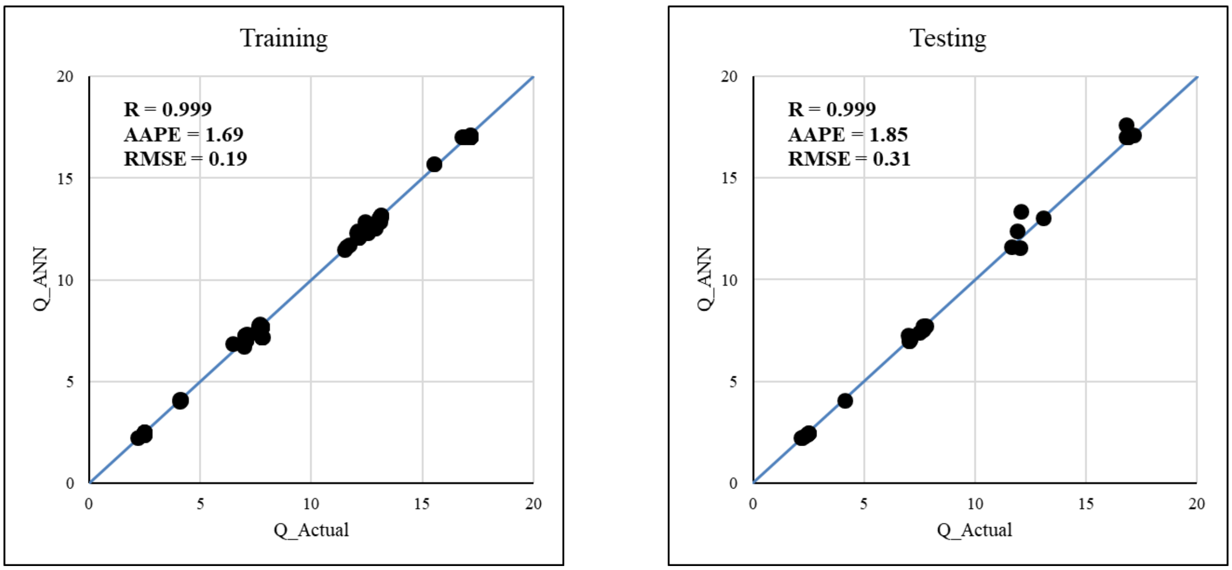

Figure 4: The actual and predicted flow rates for training and testing.

To prove the model's generalization, a cross-validation phase was conducted. The dataset was randomly partitioned into five segments, with four used for training and one for testing. This process was repeated five times, rotating the testing section each time. This approach ensured thorough validation of the model's accuracy. The results revealed consistent performance across all partitions, with nearly similar R, AAPE, and RMSE values. These results confirm the model's stability, robustness, and applicability.

Overfitting was evident in models with several hidden layers, as the testing error increased while the training error decreased. The best generalization on the testing dataset was obtained with a single hidden layer design consisting of five neurons. With a R value of +0.99 and an AAPE of 1.85% during testing, this comparatively straightforward structure shows that the fundamental relationships in the data were effectively represented without needless complication. This strong generalization was further reinforced by the selection of the Bayesian regularization backpropagation technique, which successfully penalizes excessively intricate weight configurations during training.

The established black-box model was turned into a transparent white-box model by deriving the ANN correlation, which can be directly applied without the need to run the AI algorithm again. This transformation involved using the normalized parameters and extracting the optimum weights and biases, as illustrated generally in Eq. 1:

$$Q_n = b_2 + \sum_{i=1}^{N} w_{2_i} . f\left(w_{1_i} . \emptyset_n + b_{1_i}\right) \quad (1)$$

where Q_n is the normalized output flow rate, *i* denotes the index of neuron, *N* is the total neurons count, and $Ø_n$ indicates the normalized input parameters array. The weights of the input and output layers are denoted by w_1 and w_2, respectively, whereas b_1 and b_2 are the biases of the two layers. The normalized parameters were ordinarily determined from the below Eq. 2 with the minimum and maximum values for any (X) parameter from Table **1**.

$$\mathrm{X}_n = 2\left(\frac{\mathrm{X} - \mathrm{X}_{min}}{\mathrm{X}_{max} - \mathrm{X}_{min}}\right) - 1 \tag{2}$$

The normalized input parameters were derived by substituting their minimum and maximum values, and expressed as follows:

$$D_{ch_n} = 0.0179\,(D_{ch} - 16) - 1 \tag{3}$$

$$T_n = 0.0694\,(T - 535.2) - 1 \tag{4}$$

$$P_{up_n} = 0.0015\,(P_{up} - 520) - 1 \tag{5}$$

$$P_{d_n} = 0.005\,(P_d - 100) - 1 \tag{6}$$

$$\gamma_n = 45.454\,(\gamma - 0.59) - 1 \tag{7}$$

The definition of the function (*f*) in Eq. 1 depends on the used transfer function on the ANN algorithm, such as *tansig*, *logsig*, *radbas*, … etc. Since the optimal model was obtained using *tansig* function, Eq. 1 would be written as follows:

$$Q_n = b_2 + \sum_{i=1}^{N} w_{2_i} \times \left(\frac{2}{1+e^{-2\left(w_{1_{i,1}} \times D_{ch_n} + w_{1_{i,2}} \times T_n + w_{1_{i,3}} \times P_{up_n} + w_{1_{i,4}} \times P_{d_n} + w_{1_{i,5}} \times \gamma_n + b_{1_i}\right)}} - 1\right) \tag{8}$$

To determine the required gas flow rate, the Q_n was denormalized by rearranging Eq. 2 as follows:

$$\mathrm{Q} = \frac{(Q_n+1)}{2}\left(Q_{max} - Q_{min}\right) + Q_{min} \tag{9}$$

By substituting Eq. 8 into Eq. 9 and using the values from Table **1**, the final derivation would be as shown in the below correlation:

$$Q = 9.67 + 7.5\left[b_2 + \sum_{i=1}^{N} w_{2_i}\left(\frac{2}{1+e^{-2\left(w_{1_{i,1}} \times D_{ch_n} + w_{1_{i,2}} \times T_n + w_{1_{i,3}} \times P_{up_n} + w_{1_{i,4}} \times P_{d_n} + w_{1_{i,5}} \times \gamma_n + b_{1_i}\right)}} - 1\right)\right]. \tag{10}$$

The optimum weights and biases that required in the above-mentioned Eq. 10 were extracted from the ANN model and presented in Table **3** hereunder.

Table 3: The weights and biases from the ANN model.

i	$w_{1\,i,1}$	$w_{1\,i,2}$	$w_{1\,i,3}$	$w_{1\,i,4}$	$w_{1\,i,5}$	w_2	b_1	b_2
1	0.842	0.755	1.176	1.730	0.518	1.731	-0.920	-0.967
2	-1.416	-0.016	0.381	-1.139	2.008	-1.793	-0.690	
3	0.563	0.045	1.012	-2.484	0.008	-2.158	0.014	
4	0.697	-0.436	1.755	-0.905	-0.438	2.257	1.553	
5	-1.938	-0.033	0.337	-1.987	1.438	2.234	-0.796	

To verify the reliability of the obtained correlation (Eq. 10), it was tested on the 10% of the dataset that had been kept unseen during model development. This validation demonstrated high accuracy, with an R value of 0.999, an AAPE of 2.78%, and an RMSE of 0.24, as illustrated in the cross plot in Fig. (**5**).

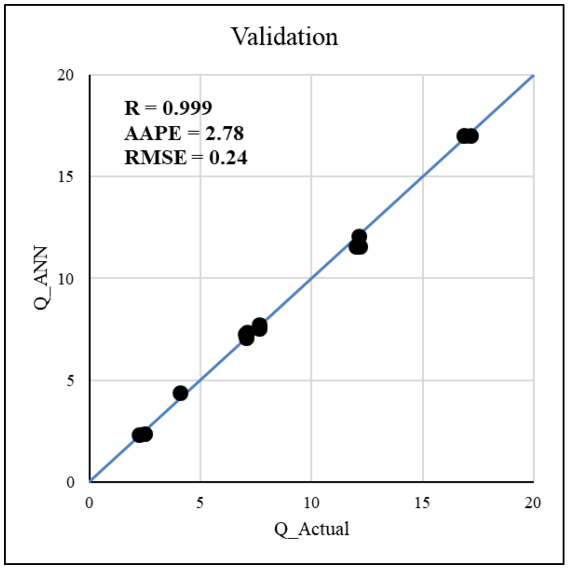

Figure 5: The actual and predicted flow rates for validation dataset.

This study explores the use of ANN as an effective tool for optimizing natural gas flow rates through surface well chokes, considering well pressure, temperature, and fluid properties. By leveraging the capabilities of the ANN model, we transform raw data into actionable insights, significantly enhancing our understanding and management of gas flow dynamics. However, a key limitation of this model is data availability; the input data must fall within the ranges specified in Table **1**. If the data deviates from these ranges, the accuracy of the results may decrease significantly.

4. Conclusion

This study successfully developed an ANN model using over 150 data points from a gas field, incorporating variables such as choke size, tubing temperature, upstream and downstream pressures, gas specific gravity, and gas flow rates. These inputs, selected based on empirical correlations and gas law principles, were used to predict gas flow rates effectively. The dataset was meticulously analyzed and cleaned to ensure data representation, reliability, and quality, confirming its comprehensive coverage and alignment with expected ranges.

The relative importance of each parameter was evaluated, showing high correlation values for choke size and pressures, while tubing temperature and gas specific gravity, despite lower correlation coefficients, were still significant. The optimal model configuration included 5 neurons in a single hidden layer with Bayesian regularization backpropagation and hyperbolic tangent sigmoid function. The developed model achieved high accuracy with R value of +0.99, AAPE of 1.69% and 1.85%, and RMSE of 0.19 mmscf/d and 0.31 mmscf/d for training and testing, respectively. Cross-validation confirmed the model's stability and reliability across different data partitions.

Robust generalization was demonstrated by the outstanding accuracy with which this equation was evaluated on unknown data (R=0.999, AAPE=2.78%). This research offers field engineers a straightforward way to optimize choke settings in real-time, maximizing production efficiency, guaranteeing reservoir integrity, and assisting with the digital transformation of well management practices by offering a dependable and instantaneous calculation method. Compared to conventional empirical methods, the suggested model and its resulting correlation provide a better, more useful option.

The ANN model was transformed into a transparent white-box model, deriving an empirical equation that could be used directly with the derived weights and biases. This transformation enhances the practical applicability of the model without needing to rerun the AI algorithm. However, the model's effectiveness is contingent on data availability, requiring input data to fall within specified ranges to maintain accuracy.

Conflict of Interest

The Authors declare no conflict of interest.

Funding

This research received no external funding.

Acknowledgments

The authors would like to acknowledge the College of Petroleum Engineering & Geosciences at the King Fahd University of Petroleum & Minerals for providing the support to conduct this research.

Author Contributions

Ashraf Ahmed: Conceptualization, methodology, software, formal analysis, resources, data curation, writing—original draft preparation, writing—review and editing.

Ahmed Abdulhamid Mahmoud: Methodology, software, formal analysis, resources, writing—original draft preparation, writing—review and editing, supervision.

Murtada A. Elhaj: Conceptualization, methodology, validation, formal analysis, resources, writing—review and editing.

Salaheldin Elkatatny: Methodology, formal analysis, investigation, resources, visualization, writing—review and editing, supervision.

All authors have read and agreed to the published version of the manuscript.

References

[1] Nejatian I, Kanani M, Arabloo M, Bahadori A, Zendehboudi S. Prediction of natural gas flow through chokes using support vector machine algorithm. J Nat Gas Sci Eng. 2014; 18: 155-63. https://doi.org/10.1016/j.jngse.2014.02.008

[2] Wu J, Yang X, Di Y, Li P, Zhang J, Zhang D. Numerical simulation of choke size optimization in a shale gas well. Geofluids. 2022; 2022: 1-12. https://doi.org/10.1155/2022/2197001

[3] Naseri S, Tatar A, Shokrollahi A. Development of an accurate method to prognosticate choke flow coefficients for natural gas flow through nozzle and orifice type chokes. Flow Meas Instrum. 2016; 48: 1-7. https://doi.org/10.1016/j.flowmeasinst.2015.12.003

[4] Guo L, Wang Y, Xu X, Gao H, Yang H, Han G. Study on the erosion of choke valves in high-pressure, high-temperature gas wells. Processes. 2022; 10(10): 2139. https://doi.org/10.3390/pr10102139

[5] Al-Attar H. Performance of wellhead chokes during sub-critical flow of gas condensates. J Pet Sci Eng. 2008; 60(3-4): 205-12. https://doi.org/10.1016/j.petrol.2007.08.001

[6] Naseri S, Tatar A, Shokrollahi A. Development of an accurate method to prognosticate choke flow coefficients for natural gas flow through nozzle and orifice type chokes. Flow Meas Instrum. 2016; 48: 1-7. https://doi.org/10.1016/j.flowmeasinst.2015.12.003

[7] Elhaj MA, Anifowose F, Abdulraheem A. Single gas flow prediction through chokes using artificial intelligence techniques. In: SPE Saudi Arabia Section Annual Technical Symposium & Exhibition; 21-23 April 2015; Al-Khobar, Saudi Arabia. Society of Petroleum Engineers; 2015. https://doi.org/10.2118/177991-MS

[8] Choubineh A, Ghorbani H, Wood DA, Robab Moosavi S, Khalafi E, Sadatshojaei E. Improved predictions of wellhead choke liquid critical-flow rates: Modelling based on hybrid neural network training learning based optimization. Fuel. 2017; 207: 547-60. https://doi.org/10.1016/j.fuel.2017.06.131

[9] Ghorbani H, Moghadasi J, Wood DA. Prediction of gas flow rates from gas condensate reservoirs through wellhead chokes using a firefly optimization algorithm. J Nat Gas Sci Eng. 2017; 45: 256-71. https://doi.org/10.1016/j.jngse.2017.04.034

[10] Gidado AO, Adeniyi AT, Olusola B, Giwa A. Sensitivity analysis of choke size selections on reservoir pressure drawdown using Prosper modelling for reservoir management. In: The SPE Nigeria Annual International Conference and Exhibition; 2023; Lagos, Nigeria. Society of Petroleum Engineers; 2023. https://doi.org/10.2118/217146-MS

[11] Ahmed A, Mahmoud AA, Elhaj MA, Elkatatny S. Artificial neural networks for optimization of natural gas flow through surface well chokes. In: Society of Petroleum Engineers ADIPEC 2024; 4 Nov 2024; Abu Dhabi, UAE. Society of Petroleum Engineers; 2024. https://doi.org/10.2118/222586-MS (cited 2025 Nov 1).

[12] Nasriani HR, Khan K, Graham T, Ndlovu S, Nasriani M, Mai J, *et al*. An investigation into sub-critical choke flow performance in high rate gas condensate wells. Energies (Basel). 2019; 12(20): 3992. https://doi.org/10.3390/en12203992

[13] Seidi S, Sayahi T. A new correlation for prediction of sub-critical two-phase flow pressure drop through large-sized wellhead chokes. J Nat Gas Sci Eng. 2015; 26: 264-78. https://doi.org/10.1016/j.jngse.2015.06.025

[14] Khorzoughi MB, Beiranvand MS, Rasaei MR. Investigation of a new multiphase flow choke correlation by linear and non-linear optimization methods and Monte Carlo sampling. J Pet Explor Prod Technol. 2013; 3(4): 279-85. https://doi.org/10.1007/s13202-013-0067-9

[15] Sadri M, Mahdiyar H, Mohsenipour A. A compositional thermal multiphase wellbore model for use in non-isothermal gas lifting. J Energy Resour Technol. 2019; 141(11): 1-12. https://doi.org/10.1115/1.4043653

[16] Nascimento JCS, Santos A dos, Pico Ortiz CE, Pires AP. A fully implicit EOS based compositional two-phase transient flow simulator in wellbores. J Pet Sci Eng. 2021; 205: 108923. https://doi.org/10.1016/j.petrol.2021.108923

[17] Choubineh A, Ghorbani H, Wood DA, Robab Moosavi S, Khalafi E, Sadatshojaei E. Improved predictions of wellhead choke liquid critical-flow rates: Modelling based on hybrid neural network training learning based optimization. Fuel. 2017; 207: 547-60. https://doi.org/10.1016/j.fuel.2017.06.131

[18] Al-Khalifa MA, Al-Marhoun MA. Application of neural network for two-phase flow through chokes. In: The SPE Saudi Arabia Section Technical Symposium & Exhibition; May 2013; Al-Khobar, Saudi Arabia. Society of Petroleum Engineers; 2013. https://doi.org/10.2118/169597-MS

[19] Khamis M, Elhaj M, Abdulraheem A. Optimization of choke size for two-phase flow using artificial intelligence. J Pet Explor Prod Technol. 2020; 10(2): 487-500. https://doi.org/10.1007/s13202-019-0734-6

[20] Siddig O, Abdulhamid Mahmoud A, Elkatatny S, Soupios P. Utilization of artificial neural network in predicting the total organic carbon in devonian shale using the conventional well logs and the spectral gamma ray. Comput Intell Neurosci. 2021; 2021: 1-12. https://doi.org/10.1155/2021/2486046

[21] Mahmoud AA, Elkatatny S, Ali A, Moussa T. Estimation of static young's modulus for sandstone formation using artificial neural networks. Energies (Basel). 2019; 12(11): 2125. https://doi.org/10.3390/en12112125

[22] Al-AbdulJabbar A, Mahmoud AA, Elkatatny S. Artificial neural network model for real-time prediction of the rate of penetration while horizontally drilling natural gas-bearing sandstone formations. Arab J Geosci. 2021; 14(2): Article no. 117. https://doi.org/10.1007/s12517-021-06457-0

[23] Al-AbdulJabbar A, Mahmoud AA, Elkatatny S, Abughaban M. A novel artificial neural network-based correlation for evaluating the rate of penetration in a natural gas bearing sandstone formation: a case study in a middle east oil field. J Sens. 2022; 2022: 1-14. https://doi.org/10.1155/2022/9444076

[24] Hassoun MH, Intrator N, McKay S, Christian W. Fundamentals of artificial neural networks. Comput Phys. 1996; 10(2): 137-137. https://doi.org/10.1063/1.4822376

[25] Pircher T, Pircher B, Schlücker E, Feigenspan A. The structure dilemma in biological and artificial neural networks. Sci Rep. 2021; 11(1): 5621. https://doi.org/10.1038/s41598-021-84813-6

[26] Alaloul SW, Qureshi HA. Data Processing Using Artificial Neural Networks. In: Harkut D, Ed. Dynamic Data Assimilation - Beating the Uncertainties. IntechOpen; 2020. https://doi.org/10.5772/INTECHOPEN.92194

[27] Qamar R, Ali Zardari B. Artificial neural networks: an overview. Mesopotamian J Comput Sci. 2023; 2023: 130-9. https://doi.org/10.58496/MJCSC/2023/015

[28] Ismail A, Ewida HF, Nazeri S, Al-Ibiary MG, Zollo A. Gas channels and chimneys prediction using artificial neural networks and multi-seismic attributes, offshore West Nile Delta, Egypt. J Pet Sci Eng. 2022; 208: 109349. https://doi.org/10.1016/j.petrol.2021.109349

[29] Li S, Liu B, Ren Y, Chen Y, Yang S, Wang Y, *et al*. Deep-learning inversion of seismic data. IEEE Trans Geosci Remote Sens. 2020; 58(3): 2135-49. https://doi.org/10.1109/TGRS.2019.2953473

[30] Peters B, Haber E, Granek J. Neural networks for geophysicists and their application to seismic data interpretation. The Leading Edge. 2019; 38(7): 534-40. https://doi.org/10.1190/tle38070534.1

[31] Al-AbdulJabbar A, Mahmoud AA, Elkatatny S. Artificial neural network model for real-time prediction of the rate of penetration while horizontally drilling natural gas-bearing sandstone formations. Arab J Geosci. 2021; 14(2): 117. https://doi.org/10.1007/s12517-021-06457-0

[32] Al-AbdulJabbar A, Mahmoud AA, Elkatatny S, Abughaban M. Artificial neural networks-based correlation for evaluating the rate of penetration in a vertical carbonate formation for an entire oil field. J Pet Sci Eng. 2022; 208: 109693. https://doi.org/10.1016/j.petrol.2021.109693

[33] Alkinani HH, Al-Hameedi ATT, Dunn-Norman S, Lian D. Application of artificial neural networks in the drilling processes: Can equivalent circulation density be estimated prior to drilling? Egypt J Pet. 2020; 29(2): 121-6. https://doi.org/10.1016/j.ejpe.2019.12.003

[34] Ashena R, Rabiei M, Rasouli V, Mohammadi AH, Mishani S. Drilling parameters optimization using an innovative artificial intelligence model. J Energy Resour Technol. 2021; 143(5): 052110. https://doi.org/10.1115/1.4050050

[35] Mahmoud AA, Elkatatny S, Ali A, Moussa T. Estimation of static young's modulus for sandstone formation using artificial neural networks. Energies (Basel). 2019; 12(11): 2125. https://doi.org/10.3390/en12112125

[36] Mahmoud AA, Gamal H, Elkatatny S, Alsaihati A. Estimating the total organic carbon for unconventional shale resources during the drilling process: a machine learning approach. J Energy Resour Technol. 2022; 144(4): 043004. https://doi.org/10.1115/1.4051737

[37] Ahmed AA, Elkatatny S, Abdulraheem A, Mahmoud M. Application of artificial intelligence techniques in estimating oil recovery factor for water derived sandy reservoirs. In: SPE Kuwait Oil & Gas Show and Conference; Oct 2017; Kuwait City, Kuwait. Society of Petroleum Engineers; 2017. Paper No. SPE-187621-MS. https://doi.org/10.2118/187621-MS

[38] Saikia P, Baruah RD, Singh SK, Chaudhuri PK. Artificial neural networks in the domain of reservoir characterization: A review from shallow to deep models. Comput Geosci. 2020; 135: 104357. https://doi.org/10.1016/j.cageo.2019.104357

[39] Aminian K, Ameri S. Application of artificial neural networks for reservoir characterization with limited data. J Pet Sci Eng. 2005; 49(3-4): 212-22. https://doi.org/10.1016/j.petrol.2005.05.007

[40] Mohaghegh S, Arefi R, Ameri S, Aminiand K, Nutter R. Petroleum reservoir characterization with the aid of artificial neural networks. J Pet Sci Eng. 1996; 16(4): 263-74. https://doi.org/10.1016/S0920-4105(96)00028-9

[41] Elkatatny S, Al-AbdulJabbar A, Mahmoud AA. New robust model to estimate formation tops in real time using artificial neural networks (ANN). Petrophysics. 2019; 60(6): 825-37. https://doi.org/10.30632/PJV60N6-2019a7

[42] Vo Thanh H, Sugai Y, Sasaki K. Application of artificial neural network for predicting the performance of CO2 enhanced oil recovery and storage in residual oil zones. Sci Rep. 2020; 10(1): 18204. https://doi.org/10.1038/s41598-020-73931-2

[43] Cheraghi Y, Kord S, Mashayekhizadeh V. Application of machine learning techniques for selecting the most suitable enhanced oil recovery method; challenges and opportunities. J Pet Sci Eng. 2021; 205: 108761. https://doi.org/10.1016/j.petrol.2021.108761

[44] Fujii H, Shirai H, Doi M, Sugai K. Optimization of oil production schemes in actual oil fields with application of artificial neural networks on reservoir simulation. J Japan Assoc Pet Technol. 2009; 74(2): 175-84. https://doi.org/10.3720/japt.74.175

[45] Ansari A, Heras M, Nones J, Mohammadpoor M, Torabi F. Predicting the performance of steam assisted gravity drainage (SAGD) method utilizing artificial neural network (ANN). Petroleum. 2020; 6(4): 368-74. https://doi.org/10.1016/j.petlm.2019.04.001

[46] Elhaj MA, Enamul Hossain M, Imtiaz SA, Naterer GF. Hysteresis of wettability in porous media: a review. J Pet Explor Prod Technol. 2020; 10(5): 1897-905. https://doi.org/10.1007/s13202-020-00872-x

[47] Choubineh A, Ghorbani H, Wood DA, Robab Moosavi S, Khalafi E, Sadatshojaei E. Improved predictions of wellhead choke liquid critical-flow rates: Modelling based on hybrid neural network training learning based optimization. Fuel. 2017; 207: 547-60. https://doi.org/10.1016/j.fuel.2017.06.131

[48] ZareNezhad B, Aminian A. An artificial neural network model for design of wellhead chokes in gas condensate production fields. Pet Sci Technol. 2011; 29(6): 579-87. https://doi.org/10.1080/10916460903551065

[49] Alghamdi A, Ayoola O, Mulhem K, Otaibi M, Abdulraheem A. Real-time prediction of choke health using production data integrated with AI. In: Offshore Technology Conference; Aug 2021; Virtual and Houston, Texas, USA. Offshore Technology Conference; 2021. Paper No. OTC-30981-MS. https://doi.org/10.4043/30981-MS

[50] Dabiri MS, Hadavimoghaddam F, Ashoorian S, Schaffie M, Hemmati-Sarapardeh A. Modeling liquid rate through wellhead chokes using machine learning techniques. Sci Rep. 2024; 14(1): 1-19. https://doi.org/10.1038/s41598-024-54010-2

[51] Wang Q, Hussein MA, Kanabar B, Yadav A, Rajiv A, Shankhyan A, *et al*. Precise prediction of choke oil rate in critical flow condition via surface data. J Pet Explor Prod Technol. 2025; 15(7): 1-18. https://doi.org/10.1007/s13202-025-02013-8

[52] Kaleem W, Tewari S, Fogat M, Martyushev DA. A hybrid machine learning approach based study of production forecasting and factors influencing the multiphase flow through surface chokes. Petroleum. 2024; 10(2): 354-71. https://doi.org/10.1016/j.petlm.2023.06.001