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Application of Machine Learning to Choke Performance

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ABSTRACT

The complexity of predicting hydrocarbon flow in anisotropic reservoir is exacerbated by imprecise empirical models, thus nurturing the view of utilizing multiple linear regression and artificial neural network models in this research work, taking into consideration production variables; tubing pressure, liquid flow rate, gas-oil ratio, oil specific gravity, water cut, line pressure, choke size and gas-liquid ratio in predicting choke size and flowrate under critical flow conditions. For critical flow rate represents a threshold above which solid and fines production increases significantly, which could lead to sand- related issues that can be exacerbated by factors like high flow rates and water coning, negatively impacting oil and gas production. At critical flow condition, the fluid velocity reaches the speed of sound, causing pressure waves to propagate through the flow at sonic velocity. The effectiveness of the waves beyond this point tends to be lost and changes due to downstream pressure no longer have an impact on flow rate. Thus, in applying machine learning in developing predictive models for flow rate and choke size, examining correlations between production variables and comparing predicted outcomes with actual data, a better performance model was observed for the artificial neural network model, with R^2 = 0.9451 for flow rate and R^2 = 0.9839 for choke size, which reflects the positive quality of the model. Also, the results showed a low error level per data point indicated by the mean absolute relative error of 14% for choke size and 27% for flow rate forecasting.

Keywords: Machine learning; Artificial neural network; Multiple linear regression; Choke size; Flowrate

Nomenclature: GOR= gas- oil ratio; GLR= gas- liquid ratio; OSG= oil specific gravity; tStat= Test statistic; Pwh= Tubing pressure; p- value= Probability value; F- statistic= Fisher's statistics; ANN= Artificial Neural Network

Introduction

The examination of production data is made more difficult by significant imprecision found in empirical fitting models and correlations that are used to anticipate hydrocarbon flow in reservoirs with heterogeneous and anisotropic characteristics. The behavior of hydrocarbon reservoirs, both static and dynamic, influences the production of multiphase fluids through surface chokes[1]. In managing this challenge, understanding the complex relationships that exist between different variables by researchers has been made possible with the use of machine learning (ML) techniques. These machine learning techniques have produced more accurate prediction models that are useful in many domains, including reservoir characterization, drilling automation and the classification of lithofacies[2]. Machine learning, a subset of artificial intelligence can be used to generate an expert system that can be utilized in evaluating choke performance. A choke which is a component of a well is used to maintain flow rates in the face of changes in flow line pressure, thus limiting flowrates to prevent gas or water from coning, eliminate sand problems triggered by rapid drawdown and manage production rates to prevent surface equipment from slugging. The wellhead choke in controlling the wellhead pressure, in turn influences the production rate and flowing bottom-hole pressure[3].

Flow regimes that are largely governed by the pressure differential across the choke are subcritical and critical (choked) flow. The distinct behaviors between these regimes makes it crucial that one distinguishes between these regimes when estimating flow rates. Critical flow is recognized as when a fluid velocity reaches sonic speed and the pressure waves generated due to fluctuating pressures traverse the flow at the speed of sound. In this flowing condition, the waves are rendered ineffective as the fluid advances faster. The flow rate at this condition becomes independent of downstream pressure and is uninfluenced by shifts in downstream pressure[4]. It is noted to exist when the pressure upstream of the wellhead is at least 70% higher than the pressure downstream of the wellhead or when the ratio of downstream pressure to upstream pressure is 0.588.

Taking into consideration the view of controlling solid and fines production in a well production flow stream, critical flow rate is a production threshold rate above which uniform production of solids contained within the produced flow stream is observed. In reservoirs prone to sand or fines production it is essential to maintain sub- critical flow conditions as when the flow rate exceeds this threshold (i.e., becomes critical), the production of sand and fines increases substantially.

Sand-related issues adversely affect the recovery rate in oil and gas production. High flowrate, which is influenced by drawdown, as well as the occurrence of gas or water coning are the main causes of these issues. Sand-related concerns can lead to substantial annual financial losses for producers through triggering damage to subsea and downhole equipment, surface production facilities and an increased risk of catastrophic failure. In regard to this, creating a dependable estimating model that can analyze a choke effectiveness is imperative. This model would leverage on algorithms trained on machine learning for prediction of optimum flow rate and choke size by taking into consideration a variety of fluid parameters. By doing this, these challenges can be tackled effectively and the system can be optimized.

High viscosity reservoir fluids, in juxtaposition to low viscosity fluids, enact a substantial frictional drag force on the formation particles, making them a significant fluid feature as sand production could result from this viscous drag in heavy oil reservoirs with high specific gravity. Further, more sand is produced correspondingly to the rise in water cut. The reason for this is that as the connate water tends to adhere to the produced water, the surface tension force declines, decreasing the cohesiveness between particles. Additionally, when the water cut rises, the relative permeability of oil reduces, necessitating an elevated differential pressure to produce the hydrocarbon fluid at the same rate. Shear force through the formation sand particles becomes stronger owing to the elevation of differential pressure near the well bottomhole. Sand production may originate from the increased strains since they could lead to instability in the sand arch encircling the perforation[5].

An important consideration, that impacts both the rate of production and the entire cumulative recovery of hydrocarbons is precisely figuring out the most suitable choke size. The daily production volume of hydrocarbon is significantly affected by the choke size. Production can be enhanced and wellhead pressure and bottomhole flowing pressure can be optimally minimized at the same time by increasing the choke size[6,7].

In addition, water coning arises when the drawdown in the immediate area of the well transcends the gravitational gradient due to the differences in density between water and hydrocarbons. Water advances vertically upward from the free water level in the area near the well, which is where this phenomenon usually occurs. This phenomenon contributes to liquid loading[8].

Basically, a lot of methods for figuring out flow rates through chokes have been published, however, it appears to be clear that there is still yet any approach that can predict flow characteristics with a high level of accuracy all through the whole range of typical operating circumstances found in the oil and gas sector **(Table 1)**. Thus, it is evident that developing a model with the various production variables considered using machine learning approach to forecast choke performance is essential[9].

Table 1: Summary of literature review and gap analysis.

Authors and year of publication	Findings	Gap analysis
[10]	Employed in this research work is the use of gray- box modeling to achieve an oil rate prediction with error ranging from 1.8% to 40.6%.	This analysis didn't take into consideration water cut and oil specific gravity.
[11]	This research work used stacked ensemble supervised machine learning to predict flow rate with a mean absolute percentage error of 8.1%.	This work didn't take into consideration water cut.
[12]	It was inferred in this research work that random forest (RF) model accurately replicates the actual rates under both critical and subcritical flow conditions, whereas support vector machine (SVM) model generally captured the oil rate trends but occasionally missed abrupt changes in the trend.	This work didn't take into consideration oil specific gravity and temperature.
[13]	In using a linear regression approach for forecasting oil production, a mean absolute error of 0, MSE of 0.2 and RMSE of 0.3 was achieved.	Parameter such as water cut was not considered.
[14]	In comparing the various models developed using multiple linear regression, polynomial linear regression, support vector method, decision tree regression, random forest, XGBoost, recurrent neural network and artificial neural network, it was noted that an outstanding R^2 value of 0.96 for XGBoost, 0.97 for ANN and 0.98 for RNN was achieved.	The analysis didn't consider oil specific gravity.
[15]	The simple plotting technique proposed was able to predict well gas rate using choke opening and wellhead flowing pressure with an absolute average percent deviation of 5%.	Factors such as water- cut and gas liquid ratio was not taken into consideration.

[16]	In utilizing artificial intelligence techniques such as artificial neural networks, fuzzy logic (FL), support vector machines and functional networks in estimating choke size, fuzzy logic was considered to yield the best result with a R^2 value of 1.000 for training and 0.810 for testing.	The analysis didn't not take into consideration water- cut.
[17]	The model developed using artificial neural network indicated an average absolute percent error of 3.7% in the prediction of choke size and 6.7% in the prediction of flow rate.	The analysis didn't take into consideration water- cut.
[18]	A comparative analysis of flow rate prediction performance among traditional empirical methods, machine learning techniques and deep learning algorithms was carried out with the results highlighting that deep learning algorithm surpassed other models with an R^2 value of 0.9969.	The analysis didn't not take into consideration water- cut.
[19]	Using artificial neural network, a model for estimating flow rate was developed and a correlation coefficient value of 0.89 for critical flow rate and 0.92 for subcritical flow rate was achieved.	The analysis didn't take into consideration oil specific gravity.
[20]	ANN models delivered more accurate predictions compared to empirical correlations, with coefficients of determination (R^2) of 0.9653 for the Gilbert model and 0.9951 for the modified Gilbert model.	Water cut wasn't considered
[1]	Test results indicate that the stacked generalization architecture outperformed other prominent methods considered for production forecasting	Water cut wasn't considered.
[21]	A new empirical model, derived from the Choubineh et al. model, was developed to forecast the liquid production rate of chokes in Niger Delta oil wells achieving an R^2 of 0.982.	Water cut wasn't considered
[22]	Adaboost-SVR model showed outstanding performance over other models proposed, achieving an Average Absolute Percent Relative Error (AAPRE) of 5.15% and a correlation coefficient of 0.9784.	Water cut wasn't considered

Materials and Methods

In this study, a dataset of 701 production variables; flow rate, gas- liquid ratio, oil specific gravity, choke size, upstream pressure, downstream pressure, gas- oil ratio and water cut were considered in the development of machine learning models using MATLAB software.

Assumption; for the purpose of these research work, the pressure ratio at which critical flow occurs is taken as 0.588 as indicated in the work of Hamzeh, et al[23].

Multiple linear regression

A multiple linear regression model is developed with the use of a MATLAB software.

Exploratory analysis: Processing the data involves carrying out exploratory analysis which include assessing whether there is a linear relationship between the independent and dependent variables which can be examined using scatter plots. Cross plot also known as scatter plot can be used to show the proximity of the data points, indicating their level of agreement[17,24].

Artificial neural network

Another tool that will be employed for this study is artificial neural network. The data set for an artificial neural network are partitioned into training, validation and testing data. The partitioning ratio intended for this study is 80% training, 10% validation and 10% testing[17].

Measures of evaluation

R—squared (R^2)

A higher R^2 value indicates a better performing model and also the goodness of fit of the model.

$$R^2 = \frac{\text{Model sum of squared}}{\text{Total sum of squared}} = \frac{\sum_{i=1}^{n}(\hat{y}_i - \bar{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2} \qquad \text{Eqn. i}$$

Where is the predicted outcome, is the observed outcome and is the average of observed outcomes [24].

Mean relative error (MRE)

$$\text{MRE}= \frac{1}{N}\sum_{i=1}^{N}\left(\frac{\text{Predicted}_i - \text{Actual}_i}{\text{Actual}_i}\right) x100(\%) \text{ Eqn. ii}$$

The mean relative error delineates the variance between the predicted value and the actual value and is capable of assuming positive as well as negative values. When forecasts diverge significantly from the actual value, yet are evenly dispersed between overestimations and underestimations, this discrepancy tends to approach zero, despite each individual prediction being notably inaccurate.

Mean of absolute relative error

$$\text{MARE}= \frac{1}{N}\sum_{i=1}^{N}\left|\frac{Actual - Predicted}{Actual}\right| x\ 100(\%) \text{ Eqn. iii}$$

The mean of the absolute relative error will be low only when the error associated with each data point is minimal.

Standard deviation

$$\sigma = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}\left[\left(\frac{Predicted_i - Actual_i}{Actual_i}\right) - \frac{MRE}{100}\right]^2} X100(\%) \text{ Eqn. iv}$$

The standard deviation provides insight into the degree of dispersion among the relative errors; however, if all predictions consistently overestimate by, for instance, 20 – 25%, the standard deviation will be minimal[4].

Results and Discussion

The input parameter for the model were tubing pressure (Pwh), water cut, gas- oil ratio (GOR), gas- liquid ratio (GLR), oil specific gravity (OSG) while the output parameters were flow rate and choke size[25-27].

Multiple linear regression and artificial neural network techniques were applied to develop a model for flow rate and choke size respectively[28].

Multiple linear regression

(Figure 1), is a plot that visualizes the connections and correlations between the features. The diagonal of the plot represents the data frequency for each set. The correlation coefficient between all of the data features ranges from -1 for the strong inverse relationship and 1 for a strong direct relationship. Water cut and tubing pressure showed the strongest correlation, indicating a strong direct relationship as an increase in water cut generally leads to higher tubing pressures due to changes in fluid density, viscosity and flow patterns[29,30]. While oil specific gravity and tubing pressure showed weak direct correlation as higher specific gravity oils result in higher hydrostatic pressure and potentially increased frictional losses, leading to higher overall tubing pressure. Also, oil specific gravity and flow rate showed an inverse relationship, as high oil specific gravity leads to increased pressure drops and flow resistance resulting to low flow rate in an oil well[31].

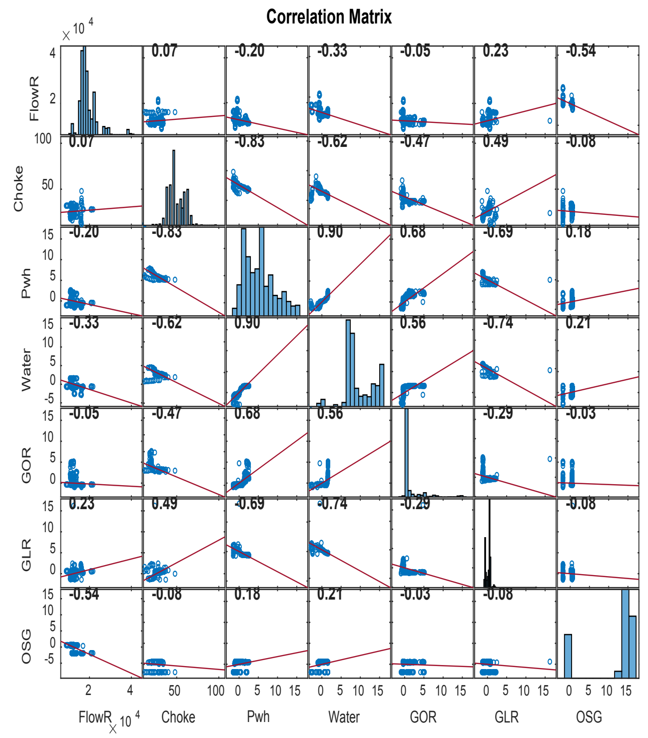

Figure 1: A correlation matrix plot of data features.

In addition, choke size and flow rate showed very low direct correlation which is indicative that increasing the choke size generally increases the flow rate but careful management is necessary to avoid reservoir damage, excessive water or gas production and equipment wear[32]. Also, the low correlation could be indicative that the flowrate is dependent on the reservoir energy. For instance, artificial lift is needed when the reservoir energy has depleted, which is indicated by a decline in tubing pressure. As observed in the correlation matrix plot, tubing pressure has a strong inverse relationship with choke size, indicative that choke size can influence tubing pressure[33,34]. That is an increase in choke size can lead to a decrease in tubing pressure and a decrease in choke size can lead to an increase in tubing pressure.

In **(Table 2)**, it is indicated that most of the parameters showed a nearly normal distribution (Pwh, choke size, water cut), while GOR, GLR and flow rate showed positive skewness and OSG showed negative skewness. High values of skewness and kurtosis for GLR, GOR and flow rate represent an asymmetric distribution for these variables with most of the data shifted to the lower end[35].

The result contained in **(Table 3)**, indicates that the regression is significant because the p-value = 8.72e-257 of the F-statistic is less than 0.05. Also, the R-squared value:0.821 indicates 82% of the total variation in predicting choke size is explained by the regression. Standard error (SE), which is a measure of unexplained variation is within the range of 0.073169 to 0.1983. The p-values of the various features (wellhead pressure, water cut, gas- oil ratio, gas- liquid ratio, oil specific gravity) were less than 0.05, which indicates that they contribute significantly in the prediction of choke size[36,37].

The result contained in **(Table 4)**, indicates that the regression is significant because the p-value = 1.8e-74 of the F- statistic is less than 0.05. Also, the R-squared value: 0.399 indicates that 40% of the total variation in predicting flow rate is explained by the regression. Standard error (SE), which is a measure of unexplained variation is within the range of 54.006 to 146.37. The p-values of the various features (wellhead pressure, water cut, gas- liquid ratio, oil specific gravity) were less than 0.05, which indicates that they contribute significantly in the prediction of flow rate.

Artificial neural network

(Figure 2), shows the result of an artificial neural network model with a level of accuracy upon confirming the performance of the model with additional testing data set to be (R= 0.9839), indicating a high degree of correlation between the predicted and actual values, meaning that as one variable changes, the other tends to change in a similar manner. It also indicates that the model effectively captured the underlying patterns in the data and could produce output that closely aligns with the actual observations. The goodness of fit of the model, shown on the regression plot indicates a very strong positive linear increasing trend as majority of the data aligns to the 45o line for the training and testing data set for prediction of choke size. The high R-value reflects positively on the quality of the model indicating that the ANN architecture, as well as the chosen parameters and features, are appropriate.

Table 2: Data Statistical Analysis.

	GOR	Pwh	Choke size	Water cut	GLR	OSG	Flow rate
No. of data points	701	701	701	701	701	701	701
Maximum	0.0029	2397	48	99.3789	0.0013	1.0703	2174
Minimum	5.2910e-06	221.7799	12	0.0914	3.3113e-06	0.9293	8786
Skewness	3.3803	0.6555	0.2549	0.0072	5.9990	-1.3431	2.1414
Kurtosis	15.0216	2.6388	3.0105	2.8599	100.2508	2.8482	9.9848

Table 3: Result of multiple linear regression model for choke size prediction.

Estimated Coefficients:

	Estimate	SE	tStat	pValue
(Intercept)	25.805	0.073169	352.67	0
x1 (Pwh)	-7.8652	0.1983	-39.663	1.13E-180
x2 (water cut)	3.186	0.18754	16.989	2.13E-54
x3 (GOR)	1.2627	0.10869	11.618	1.22E-28
x4 (GLR)	-0.38085	0.11686	-3.2591	0.0011723
x5 (OSG)	0.4359	0.078052	5.5847	3.36E-08

Number of observations: 701, Error degrees of freedom: 695

Root Mean Squared Error: 1.94

R-squared: 0.821, Adjusted R-Squared: 0.82

F-statistic vs. constant model: 637, p-value = 8.72e-257

Table 4: Result of multiple linear regression model for flowrate prediction.

Estimated Coefficients:

	Estimate	SE	tStat	pValue
(Intercept)	12365	54.006	228.95	0
x1 (Pwh)	1100.2	146.37	7.5166	1.7375e-13
x2 (water cut)	-1194.4	138.42	-8.6285	4.2095e-17
x3 (GOR)	-143.24	80.223	-1.7855	0.074614
x4 (GLR)	183.74	86.254	2.1302	0.033504
x5 (OSG)	-934.85	57.611	-16.227	1.8821e-50

Number of observations: 701, Error degrees of freedom: 695

Root Mean Squared Error: 1.43e+03

R-squared: 0.399, Adjusted R-Squared: 0.395

F-statistic vs. constant model: 92.3, p-value = 1.8e-74

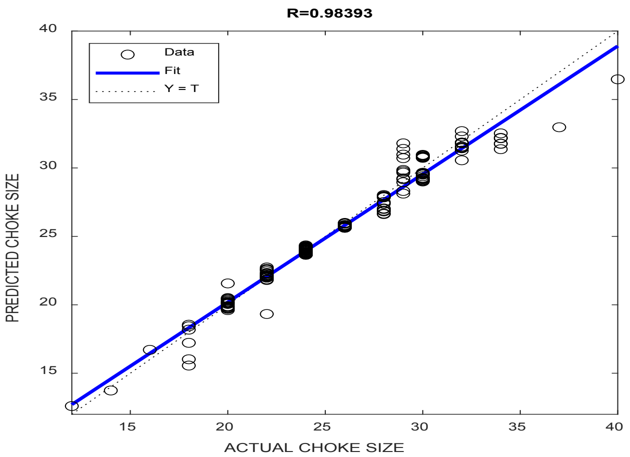

Figure 2: Regression plot for prediction of choke size.

(Figure 3), shows the result of an artificial neural network model with a level of accuracy upon confirming the performance of the model with additional testing data set to be (R= 0.9451), an indication of a very strong positive linear relationship between the predicted and actual values, which also highly reflects positively on the quality of the model that the ANN architecture, as well as the chosen parameters and features, are appropriate. The goodness of fit of the model, shown on the regression plot indicates a strong positive linear increasing trend as majority of the data aligns with the 45° line.

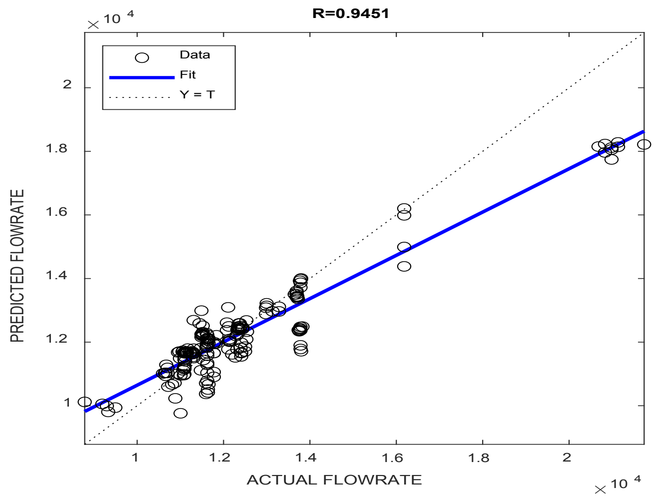

Figure 3: Regression plot for prediction of flowrate.

Evaluating the performance of the ANN models:

Table 5: Dataset for evaluation of model.

SET	Flow rate	Choke size	Pwh	Water Cut	GOR	GLR	OSG
1	11095.22	18	2372	98.795181	0.001	1.20E-05	1.063251
2	12770.83	20	1983	96.644295	0.000708	2.38E-05	0.929329
3	11442.42	22	1536	92.805755	0.0004	2.88E-05	1.069258
4	10868.79	24	1158	70	0.000295	8.84E-05	1.069965
5	12076.44	26	923	50.877193	0.000301	0.000148	1.060071
6	13284.08	28	766	49.056604	0.000259	0.000132	1.065724
7	11472.61	30	627	47.058824	0.000309	0.000163	1.069965
8	8981.849	32	499	48.421053	0.000299	0.000154	1.069117
9	12438.73	34	459	46.808511	0.000283	0.000151	1.04318

Table 6: Summary of result.

SET	**Flow rate (actual)**	**Flow rate (Predicted)**	**Choke size (actual)**	**Choke size (Predicted)**
1	11095.22	11084.11	18	18.4
2	12770.83	12872.3	20	20.2
3	11442.42	11673	22	21.8
4	10868.79	10515	24	24
5	12076.44	12750	26	26.1
6	13284.08	12800	28	28.3
7	11472.61	11400	30	30.2
8	8981.849	9555	32	32
9	12438.73	12150	34	31.7

In terms of model validation, it can be inferred that with an R value of 0.9839, the choke size model is likely generalizing well to unseen data. This means that the model is not only fitting the training data well but could also make predictions on new, unseen data as shown in **(Figure 4)**. Also, with an R value of 0.9451, the flowrate model is likely generalizing well to unseen data. This means that the model is not only fitting the training data well but could also make predictions on new, unseen data as shown in **(Figure 5)**.

As observed in **(Table 7)**, the artificial neural network model for choke size with R= 0.9839, showed high level of accuracy in predicting the target output compared to the models for flowrate with R= 0.9451 **(Table 8)**. Also, the mean of absolute relative error for choke size is 1.4% and for flow rate is 2.7%, which is an indication that the error associated with each data point is low.

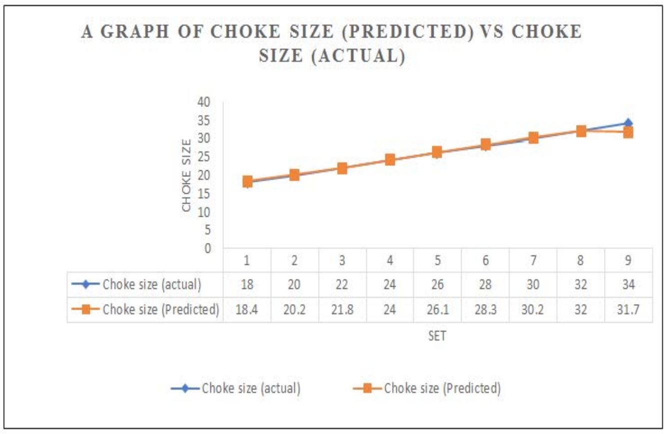

Figure 4: Evaluation of actual Vs predicted choke size.

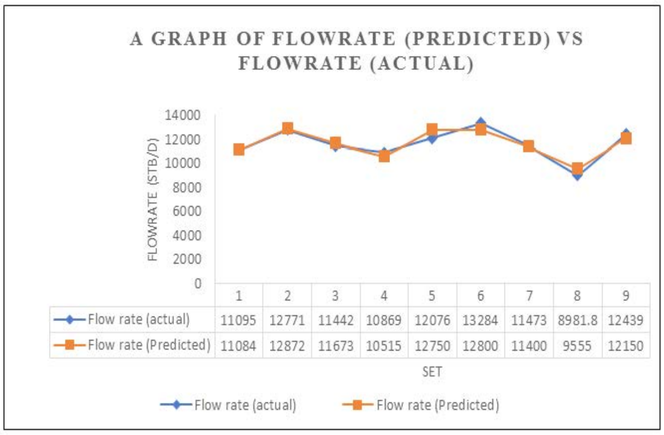

Figure 5: Evaluation of actual Vs predicted flow rate.

Table 7: Statistical evaluation of ANN models.

Model	R	Mean Relative Error	Mean of Absolute Relative Error (%)	Standard deviation (%)
CHOKE SIZE	0.9839	-0.256175	1.43206	2.589974
FLOWRATE	0.9451	0.52964015	2.719349	3.598931

Table 8: Comparison of ANN models developed with previous works.

ANN models	R2 (0.9839), MARE (1.4%), SD (2.5%) for choke size prediction model R2 (0.9451), MARE (2.7%), SD (3.5%) for flowrate prediction model
Authors	Result achieved
Hossein et al. (2021)	R2 (0.9644); AAPD (5.396); SD (697.9) using artificial nueral network for flow rate prediction
Al-Khalifa et al. (2013)	R2 (0.991); Average absolute percent error (3.7%); SD (5.56), for choke size prediction and R2 (0.986); Average absolute percent error (6.7%); SD (10.5), for flow rate prediction.
Hamzeh et al. (2018)	R2 (0.997); AAPD (7.33–8.51), SD (288.77–563.85), for flowrate prediction.

Conclusion

This study presents the application of machine learning (multiple linear regression and artificial neural network) techniques taking into consideration production variables such as tubing pressure, liquid flow rate, gas-oil ratio, oil specific gravity, water cut, line pressure, choke size and gas-liquid ratio in developing a model for predicting flow rate and choke size from which it can be deduced that, Artificial neural network models with an accuracy of R= 0.9451 for flow rate model and R= 0.9839 for choke size model was noted to be better than multiple linear regression models with R= 0.399 for flowrate model and R= 0.821 for choke size model. Also, upon evaluation of the ANN model in predicting choke size and flowrate, the mean of absolute relative error 1.4% for choke size and 2.7% for flow rate was gotten which is an indication that the measure of error associated with each data point is low.

Recommendation

The research employed 2 techniques in the development of a model for prediction of choke size and flow rate, therefore further studies could include other machine learning techniques.

A representative dataset with high measure of data accuracy and low error associated with each data point could be employed in achieving a model with a level of accuracy (R= 1.0000), as these would result to high level of accuracy of the model in predicting values.

Contribution to knowledge

This study has encouraged the understanding of how various production variables influences choke performance via the correlation matrix.

Declarations

Data availability statement

The data that support the findings of this study is openly available in Zenodo at https://doi.org/10.5281/zenodo.14226975 (Society of Petroleum Engineering data repository; Barjouei et al. 2021).

Conflicts of Interest

I, OHWOFASA JEREMIAH OSHOGBUNU, the author of the research work; Application of machine learning to choke performance, declare that there is no competing interest associated with the research work.

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References

1. Waquar K, Saurabh T, Mrigya F, Dmitriy AM. A hybrid machine learning approach-based study of production forecasting and factors influencing the multiphase flow through surface chokes. Advancing Research Evolving Science. 2023.
2. Tita R. Machine Learning Applied to Multiphase Production Problems. Stanford University 2018.
3. Boyun G. Petroleum Production Engineering Fundamentals. Petroleum Production Engineering. A computer- Assisted Approach. Elsevier Sci Techno Books 2006.
4. Haug RK. Multiphase Flow Through Chokes 2012.
5. Hisham BM, Van HL, Yuli L. Sand production: A smart control framework for risk mitigation. Advancing research evolving science 2020:1-13.
6. Yusuf AR, Wami EN, Nmegbu GC. Analyzing Wellhead Choke Sizes for Liquid Flowrate Performance Optimization. Global Scien J 2022;10(11).
7. Shadizadeh SR, Zoveidavianpoor M. A Successful Experience in Optimization of a Production Well in a Southern Iranian Oil Field. Iranian J Chem Eng 2009:37-49.
8. Miguel A. Mechanisms and control of water inflow to wells in gas reservoirs with bottom water drive.
9. Giancarlo G, Mariella L, Barbara M, Alessandro T. Numerical study of choked two-phase flow of hydrocarbons fluids through orifices. J Loss Prevention in the Process Industries 2014;27:13-20.
10. Mathilde H, Bjarne G, Dag L, Lars I. On gray-box modeling for virtual flow metering.
11. Oliver JW. Machine Learning for Well Rate Estimation: Integrated Imputation and Stacked Ensemble Modeling. Massachusetts Institute of Techno 2020.
12. Ahmed FI, Redha A, Salaheldin E, Dhafer A. Applications of Artificial Intelligence to Predict Oil Rate for High Gas-Oil Ratio and Water-Cut Wells. American Chemical Society. 2021.
13. Rehab A, Nojood A, Maryam A, Rahaf A, A'aeshah A. Prediction of Oil Production through Linear Regression Model and Big Data Tools. Int J Advanced Computer Sci Applications 2022.
14. Nehad MI, Ali AA, Turki AA, et al. Well Performance Classification and Prediction: Deep Learning and Machine Learning Long Term Regression Experiments on Oil, Gas and Water Production. MDPI 2022.
15. Ardakany M. A new plotting technique for modeling critical flow through Multi-Orifice wellhead chokes. Egyptian J Petro 2021;30:65-71.
16. Mohammad K, Murtada E, Abdulazeez A. Optimization of choke size for two phase flow using artificial intelligence. J Petro Exploration Production Techno 2019.
17. Al-Khalifa MA, Al- Marhoun MA. Application of Neural Network for Two- Phase Flow through Chokes. ResearchGate 2013.
18. Hossein B, Hamzeh G, Nima M, et al. Prediction performance advantages of deep machine learning algorithms for two phase flow rates through wellhead chokes. J Petro Exploration Production 2021.
19. Mohammed DA, Sulaiman AA, Ahmed HM. Improving Multiphase Choke Performance Prediction and Well Production Test Validation Using Artificial Intelligence; A New Milestone. ResearchGate 2015.
20. Anietie NO, Dulu A. Neural Network Models for Predicting Wellhead Pressure-Flow Rate Relationship for Niger Delta Oil Wells. J Scien Res Reports 2016:1-14.
21. Sanni KJ, Longe PO, Sylvester O. New Production Rate Model of Wellhead Choke for Niger Delta Oil Wells. J Petro Sci Techno 2020:41-49.
22. Dabiri M, Fahimeh H, Mahin S, Abdolhossein H. Modeling liquid rate through wellhead chokes using machine learning techniques. Nature 2024.
23. Hamzeh G, David W, Jamshid M, Abouzar C, Peyman A, Nima M. Predicting Liquid Flow- rate Performance Through Wellhead Chokes with Genetic and Solver Optimizers: An Oil Field case study. J Petro Exploration Production Techno 2018.
24. Ouafae, A., Yasser, M., Lahcen, O., Ahmed, D., Youssouf A. A Multiple Linear Regression-Based Approach to Predict Student Performance. Research-gate. 2020.
25. Mohamed AZ. Correlation and Regression Analysis. The Statistical, Economic and Social Research and Training Centre for Islamic Countries. 2015.
26. Shalev- Shwartz S, Ben- David S. Understanding Machine Learning: From Theory to Algorithms.
27. Rakel SA, Eline MW. Integrating Machine Learning Techniques in Real-Time Production Optimization.
28. Barjouei HS, Ghorbani H, Mohamadian N, et al. Prediction Performance Advantages of Deep Machine Learning Algorithms for Two-Phase Flow Rates Through Wellhead Chokes. J Petro Exploration and Production 2021;11:1233-1261.
29. Mursallyev A, Kushekov A, Ruslan S. Implementation of Data Driven Machine Learning Methods and Physics Driven Concepts for Real-Time Well Performance Estimation in Kashagan Field. Society of Petroleum Engineers 2019.
30. Kittilsen P, Fjalestad K, Sperle IL, Aasheim R. Robust Automatic Well Choke Control- Physical Constraint Based Operation. ScienceDirect 2016.
31. Stanley IO, Azubuike HA, Mobolaji AA, Joseph AA. The Choke as a Brainbox for Smart Wellhead Control. European J Eng Techno Res 2021.
32. Van den Hoek PJ, Geilikman MB. Prediction of Sand Production Rate in Oil and Gas Reservoirs: Importance of Bean- Up Guidelines. ResearchGate 2006.
33. Joseph A, Ajienka AJ. A Practical Approach to The Evaluation of Subcritical Multiphase Flow Through Down- Hole Safety Valves (Storm Chokes). Aca J 2014:57-69.
34. Hazim A. Performance of wellhead chokes during sub-critical 3 flow of gas condensates. J Petro Sci Eng 2007.
35. Kaydani H, Mohammad N, Ali M. Wellhead Choke Performance in Oil Well Pipeline Systems Based on Genetic Programming. J Pipeline Sys Eng Practice 2014.
36. Kargarpour MA. Oil and gas well rate estimation by choke formula: semi-analytical approach. J Petro Exploration Production Techno 2019.
37. Ehirim OE. The Efficient Use of Surface Choke to Optimize Oil Production in Niger Delta. American J Eng Res 2019:192-198.