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PREDICTING PRODUCTION FLOW RATES USING ARTIFICIAL NEURAL NETWORK – HST FIELD CASE

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A B S T R A C T

Oil production flow rate prediction is a critical aspect of oil and gas exploitation operations. Currently, flow rate forecasting is often estimated using theoretical or empirical models. Theoretical and empirical models have limitations. This study applies an Artificial neural network (ANN) for prediction flow rate. The study considered 256 datasets collected from six wells in the HST Field, Cuu Long basin. The predicted results obtained from the ANN model with eight neurons and back-propagation algorithm achieved high predictability with a strong correlation coefficient of 0.964 and a low RMSE of 32.612 bbl/d. Therefore, the developed ANN models have been promised as an effective tool in production flow rate forecasting in oilfields.

Keywords: Artificial neural network; backpropagation algorithm; flow rate prediction; multivariate regression method; gas-lift.

Introduction

Forecasting the oil production flow rate is a critical aspect of oil and gas exploitation operations. It enables timely monitoring of the well's condition and planning for drilling, repairs, and interventions necessary to ensure and maintain production. The inability to forecast the oil production rate can result in difficulties in determining how long a producing hydrocarbon facility will last and anticipating its profitability. Creating a flow forecasting model for exploiting wells is a complex and challenging task due to various production parameters and field conditions such as wellhead pressure, choke size, gas oil ratio, water cut, gas injection rate, and gas injection pressure. In order to assist with this, different theoretical and practical approaches have been developed.

Tangren et al. (1949) presented the first theoretical study on a two-phase flow regime across the choke constraints [1]. However, their approach was only effective when the liquid was in the continuous phase. Following Tangren et al. method, Gilbert (1954) proposed the empirical relation based on production well-test data and analyzed 268 data sets from Ten Section Kern County Oil fields of California for different choke sized to predict production rates at critical flow conditions [2]. The relation is given by:

$$Q = \frac{P_{wh}.S^b}{aR^c} \qquad (1)$$

where: Q is the critical-flow liquid rate (STBD); P_{wh} is the wellhead pressure (psia); S is the choke size (1/64 inch); R is the gas-liquid ratio (SCF/STB); a, b and c are empirical constants.

Several studies were developed similar relations with different empirical constants for different fields [3-5]. These relations are tabulated in table 1.

Al-Attar and Abdul-Majeed (1988) gathered data from approximately 150 wells from East Baghdad oil field (Iraq) [6]. This dataset includes various parameters such as gas-liquid ratio, wellhead pressure, choke size, production rate, and API oil gravity. To determine the most suitable correlation for estimating rates, the researchers conducted a sensitivity analysis. The findings revealed that Gilbert's correlation provided a relatively accurate prediction of the wellhead rates with an average error of 6.19%. Al-Attar (2008) developed an algorithm to forecast choke performance under subcritical conditions utilizing 97 datasets obtained from 3 wells of gas-condensate reservoir in the Middle East with various choke sizes [7].

Beiranvand et al. (2012) developed a new formula for predicting the liquid flow rate with a parameter which was not included in the Gilbert's correlation: free water, sediment and emulsion [8].

$$Q = \frac{P_{wh}.S^b.\left(1-\dfrac{BS\,\&\,W}{100}\right)^d}{aR^c} \qquad (2)$$

where: $BS\&W$ is basic sediment and water (%); a, b, c and d are the coefficients calculated based on sufficient data is available for specific reservoir with a=0.0382, b=2.151, c=0.5154, and d=0.5297.

Table 1
Empirical constants for different correlations

Correlations	Empirical constants a	Empirical constants b	Empirical constants c
Gilbert	0.1	1.89	0.546
Baxendell	0.1046	1.93	0.546
Ros	0.574	2	0.5
Achong	0.2618	1.88	0.65

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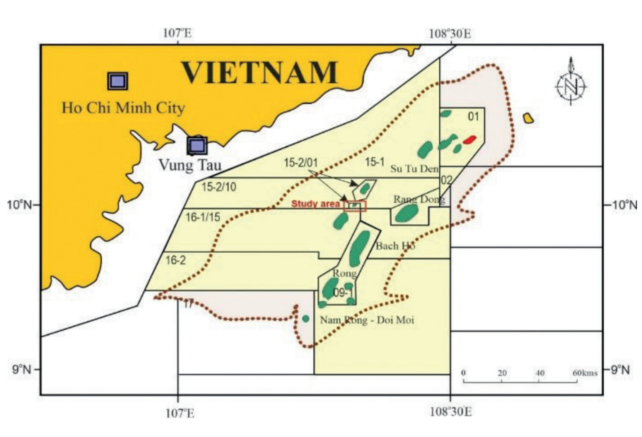

Fig. 1. Red rectangle shows the study area

Espinoza (2015) developed an adjusted empirical correlation to estimate and forecast the liquid rate in oilfields featuring consistent water-cut and naturally flowing wells [9]. This method relies on choke size, upstream wellhead pressure, and oil-gas ratio. He modified the forms of existing correlation by Gilbert and Ros. Additionally, a novel empirical coefficient was introduced to the equation to match with the historical production rate data from studied field in the Caspian Sea. However, it is important to note that this coefficient requires recalculation whenever a new test becomes accessible.

Ghorbani et al. (2018) introduced an equation that has been validated for its effectiveness in comparison to models proposed by other authors. In contrast to Beiranvand's approach of utilizing coefficient a, b, c, and d, Ghorbani et al. derived and suggested eigenfactors by analyzing 182 datasets obtained from Reshadat oil field, Lavan Island [10].

Due to the restricted of data employed in the study, the aforementioned empirical models have limitations. Each model was created for a certain area of research, which limits the range of applications for them. Because these modes frequently lacked accuracy when used in other fields, they were not widely employed.

In order to address the flaws and restrictions of both theoretical and empirical correlation methodologies, several researchers have recently turned to the application of artificial neural network (ANN) to forecast oil and gas production rates. The previous studies on using ANN to forecast liquid flow rate are presented in table 2.

The above studies show the superiority of ANN in predicting production flow rates around the world. These ANN models give results in forecasting production flow rates with high accuracy. However, in Vietnam, current studies only on traditional methods to forecast flow rate or ANN [20] to estimate production such as: utilizing the Arp equation [21] or Logistic growth model [22-24]. There has been no published study addressing the challenge of forecasting production flow rate for hydrocarbon wells based on production parameters and reservoir conditions.

In this study, the authors propose to application ANN with a back-propagation algorithm to improve prediction production flow rates of gas-lift oil wells at HST Field, Cuu Long basin (Vietnam). The forecast results will be compared with experimental equations of other published authors to evaluate the superiority of the ANN model.

Field description

The HST Field is located in south-central part of block 15-2/01 within the oil prone Cuu Long basin offshore of Vietnam. It lies approximately 120 km east of Vung Tau. The HST Field consists of a number individual stacked oil reservoir in Lower Miocene and upper part of Upper Oligocene. In general, the lithostratigraphic system is a sand dominated clastic system of fluvio-deltaic complex channel system, and lacustrine setting deposits. The quality of the oil reservoir in the Miocene is quite good with effective porosity from 15-23%, and permeability from 10-1000 mD. The test results at the HST1 well confirmed that the Miocene reservoir is a very good reservoir. HST Field is now being exploited at a flow rate of roughly 2950 bbl/d, with an average water content of about 85%.

Materials and methodology

In this study, 256 datasets were collected from six wells that are located in the HST Field. The available parameters included production flow rate, choke size, wellhead pressure, gas liquid ratio, basic sediment and water, injected gas-lift rate, injected gas-lift pressure (tab. 3).

The whole dataset from 2019 to 2020 that is collected is separated into the following three subsets: 60% of data is used for training model, 20% of data for testing model, and 20% of data for validation.

Table 2

Several machine learning applications for forecasting oil flow rate

Authors	Machine learning method	R^2	RMSE/MSE/AAPE/ARE
Gorjaei et al. (2015) [11]	Least squares support vector machine-fuzzy logic	0.976	0.8
Al-Ajmi et al. (2015) [12]	Fuzzy logic	0.94	1392
Choubineh et al. (2017) [13]	ANN	0.981	714
Ghorbani et al. (2018) [10]	Genetic algorithm and Excel's solver optimizer	0.997	303.1-562.52
Khan et al (2018) [14]	Support vector machine (SVM) and ANN	0.96-0.99	2.5618-3.7496
Barjouei et al. (2021) [16]	Deep learning,	0.9969	196
Ibrahim et al. (2021) [16]	Random forests and SVM	0.94-0.98	
Azim's study (2022) [17]	ANN	0.96	0.02
Somorotin et al. (2023) [18]	ANN	0.873	
Kaleem et al. (2023) [19]	Extra trees, Random Forest, Gradient Boosting, Decision trees…	>0.97	>60.8729

An outlier is a data point that differs significantly from other measured values. An outlier may be due to fluctuations in the measurement or it may be an indication of meter error. Finding outliers is essential because they can impair the performance of ANN model, induce overfitting or poor generalization. In order to clean and prepare the data for training and to ensure the validity of the ANN model's results, it is crucial to find outliers. In this study, to identify outliers, we use the z-score algorithm. The z value is determined by equation:

$$z = \frac{X_i - X_{mean}}{SD} \tag{3}$$

where, X_i is a value, X_{mean} is the mean value of the analyte obtained by the participants results, SD is the standard deviation of the data. According to Tripathy et al. (2013), when a data point has a z-score of greater than three or less than three, it is generally regarded as an outlier [1].

Selecting input parameters determines the accuracy and processing time in the ANN model's prediction. According to theoretical studies conducted by above authors, the initial six input parameters (tab. 3) affect the output parameter rate flow. However, to validate this, an analysis of the literature primarily relies on the correlation coefficient R^2 to assess the impact of these input parameters on the output parameter (fig. 2). This enables the accurate selection of input parameters for training ANN model.

It is observed that the correlation coefficient values for the production parameters and flow rate are all less than 0.6. This indicates that to construct a highly accurate flow rate prediction model, a comprehensive set of input parameters comprising various factors is required. Therefore, all production parameters can be utilized as an input, and regarded as contributing equally to the forecast model.

Before using the above parameters, it is necessary to standardize them to a value range from 0 to 1 according to the normalized formula:

$$Y_{Nor} = \frac{Y - Y_{min}}{Y_{max} - Y_{min}} \tag{4}$$

where: Y is the original data; Y_{Nor} – normalized data, Y_{min} – minimum data value, Y_{max} – maximum data value.

ANN is a computational model designed to imitate the transmission of signals between biological neurons. It consists of multiple interconnected neural units that work together to process information. A typical ANN usually has three layers as follows: Input, Hidden and Output.

- Input layer: information to be processed is fed into the ANN through the input layer. The input node receives, classifies, analyzes the data and then passes the data to the next layer.
- Hidden layer: data is transferred from the input layer to the hidden layer, or from one hidden layer to another. ANN can have one or more hidden layers. Each of them analyzes the output data from the previous layer, processes it further, and passes the data to next layer.
- Output layer: the output layer returns the final results of all data previously processed by ANN. This class can have one or more nodes.

The ANN model to predict flow rate for gas-lift wells in this study uses the backpropagation algorithm [14] and the production parameters will be considered as input for network training and the flow rate will be the output. In particular, the flow rate will be the output of the network, with the mining parameters serving as the input data. The neural network has two processes: forward and backward propagation phases. While the forward step sends impulses via neurons to calculate output targets, the backward step is used to generate the error vector between the actual and goal values. The network's weighted connections are modified using this error value. Until the error value hits a predetermined minimum threshold or a predetermined number of cycles have been completed, the propagation process iteratively continues. As a result, the neural network gradually converges towards producing an output that closely resembles the desired target output.

One factor that affects the precision and processing speed of ANN model's predictions is the quantity of neurons in the hidden layer (№). It is essential to carefully choose this number to ensure accurate predictions that align well with the desired output. It's crucial to use caution in order to avoid overfitting brought on by an excessive

Table 3

Data of 6 study wells

Parameters		**First dataset (2019-2020)**	**Second dataset (2021)**
Number of samples		**228**	**28**
Production flow rate, STB/day	Minimum value	95.40	198.24
	Maximum value	1092.50	880.16
	Mean value	526.51	549.46
	Standard error	270.16	226.04
Choke size, inch	Minimum value	104.00	137.00
	Maximum value	157.00	157.00
	Mean value	140.46	149.94
	Standard error	16.55	9.70
Wellhead pressure, kPag	Minimum value	2439.00	2757.00
	Maximum value	3361.00	3074.00
	Mean value	2942.37	2905.88
	Standard error	150.51	79.33
Gas liquid ratio, SCF/STB	Minimum value	140.97	417.58
	Maximum value	875.70	890.66
	Mean value	514.89	615.23
	Standard error	138.24	144.68
Basic sediment and water, %	Minimum value	75.27	82.00
	Maximum value	99.44	96.00
	Mean value	90.05	89.23
	Standard error	5.51	4.44
Injected gas-lift rate, MMSCFd	Minimum value	1.46	1.80
	Maximum value	4.00	4.00
	Mean value	2.83	3.27
	Standard error	0.54	0.94
Injected gas-lift pressure, kPag	Minimum value	9275.80	9865.00
	Maximum value	12085.00	11283.00
	Mean value	10755.62	10630.09
	Standard error	575.65	486.83

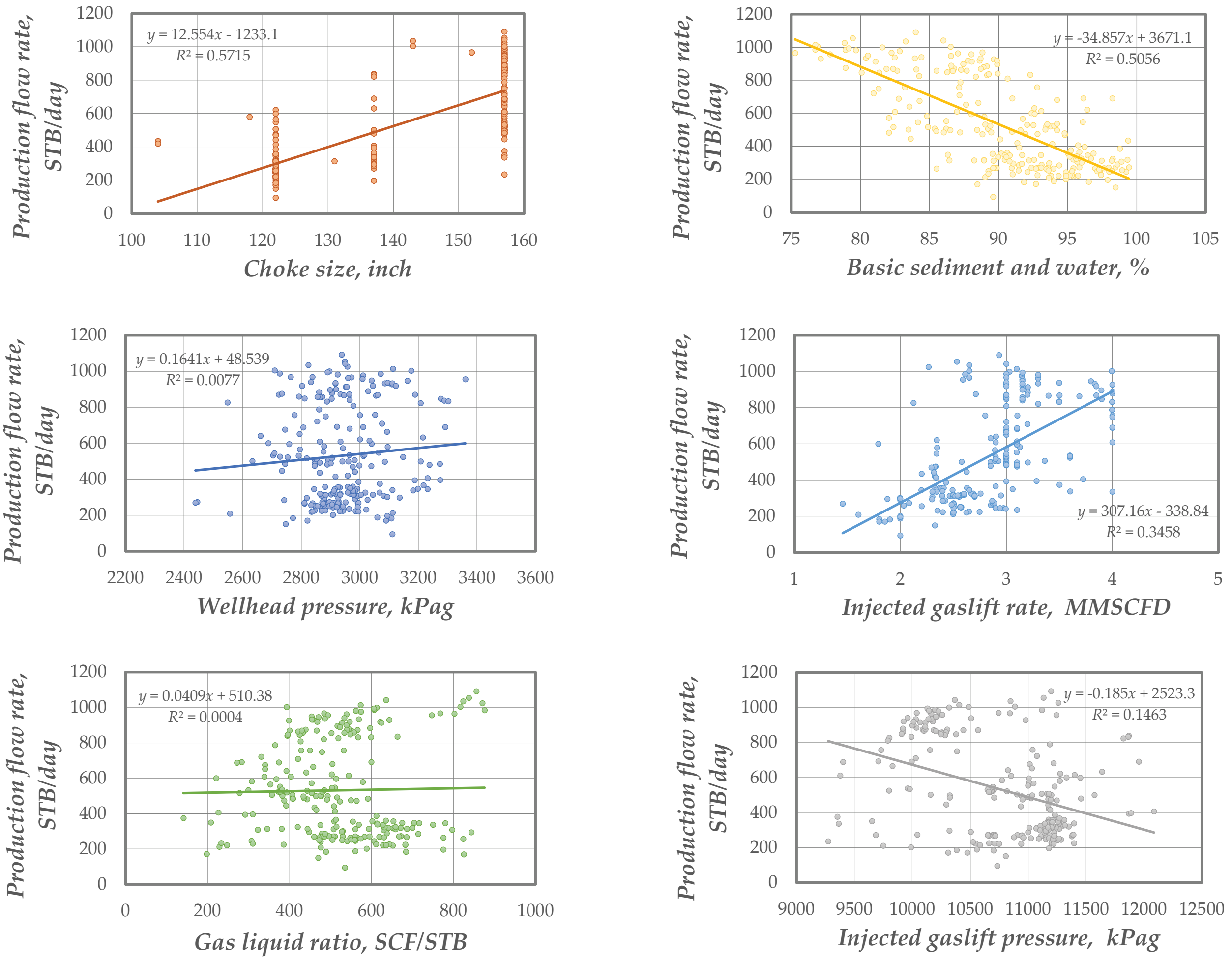

Fig. 2. Correlation coefficient R^2 between production parameters and flow rate
ANN model development for forecasting oil production flow rates

Table 4

Summary the results of R^2 and RMSE from different ANN models

№	R^2			RMSE		
	Training	Validation	Testing	Training	Validation	Testing
4	0.948	0.939	0.933	52.412	66.387	61.712
5	0.953	0.944	0.941	48.324	58.365	63.923
6	0.958	0.941	0.954	43.774	54.123	57.673
7	0.961	0.951	0.954	32.623	46.212	51.598
8	0.964	0.953	0.957	32.612	44.198	45.743
9	0.963	0.954	0.959	32.324	45.586	46.894
10	0.961	0.949	0.951	31.854	45.286	46.412

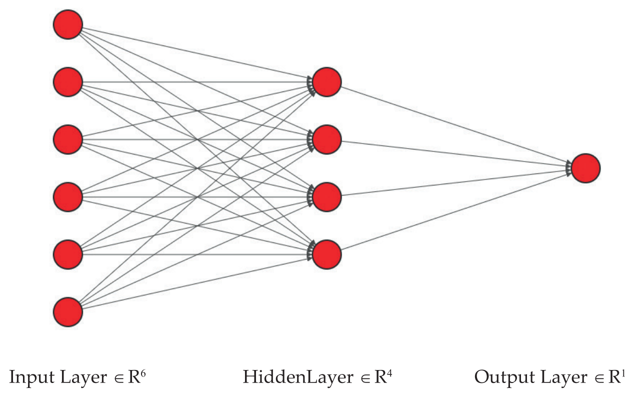

Fig.3. Structure of ANN

number of neurons in the hidden layer. Table 4 provide the results obtained from different models employing varying number of neurons in the hidden layer. When comparing R^2 and Root Mean Square Error (RMSE) values in table 2 between these models, it is clear that as the number of neurons in hidden layer increases from 4 to 7, the model's accuracy tends to steadily improve. However, when the number of neurons in hidden layer is increased further from 7 to 10, the results are not particularly noteworthy and even exhibit evidence of declining accuracy (10-neuron model). Thereby, the authors assert that ANN used for predicting the flow rate of gas-lift wells at the HST field should employ 8 neurons in hidden layer to simplify the model while still maintaining high accuracy in forecasting.

Results and discussions

To assess how successful the resulting ANN models are, the authors compared the prediction accuracy with the traditional method (The multivariate regression method) on the same dataset. This method is expressed through equation 5:

$$Q_l = x_1 D_{64} + x_2 P_{wh} + x_3 GLR + x_4 BS\&W + x_5 Q_{Glift} + x_6 P_{Glift} + y \quad (5)$$

where: x_1, x_2, x_3, x_4, x_5, x_6, and y – empirical parameters (table 5).

The correlation coefficients when predicting flow rate using the multivariate regression method and the ANN model with the actual flow rate values are presented in figure 4.

Figure 4 demonstrates that the ANN model's prediction accuracy is higher than that of the multivariate regression model. Although the ANN model provides very high accuracy results when using the dataset (2019-2020), however, to confirm the effectiveness and superiority of this model for future forecasts or for other wells, the authors decided to use this model to predict the second dataset (2021) includes 28 points (fig. 5, 6).

Although the production history of wells HST5 and HST6 in 2021 has not been used in the training process but the history matching results between the forecast results by the ANN model and the actual data still demonstrate a high match, and the future flow rate forecast curve tends to align with the actual data. This highlights the potential effectiveness and versatility of the ANN model for predicting oil production flow rate beyond the training dataset.

Table 5

Coefficients of Equation 5

Parameters	Coefficients
Intercept (y)	1463.79
x_1	4.278
x_2	0.144
x_3	0.313
x_4	-25.717
x_5	66.628
x_6	-0.0027

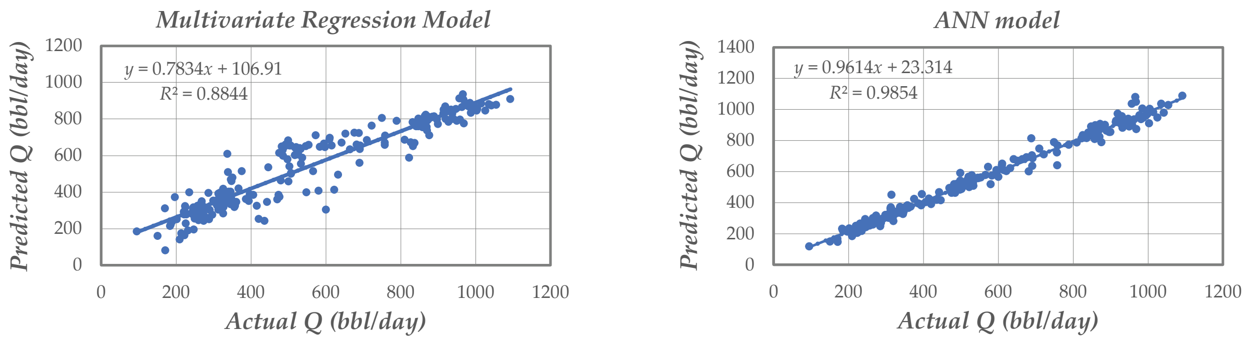

Fig. 4. Coefficient correlation R^2 of predicted values from ANN model and Multivariate regression model compared to actual values

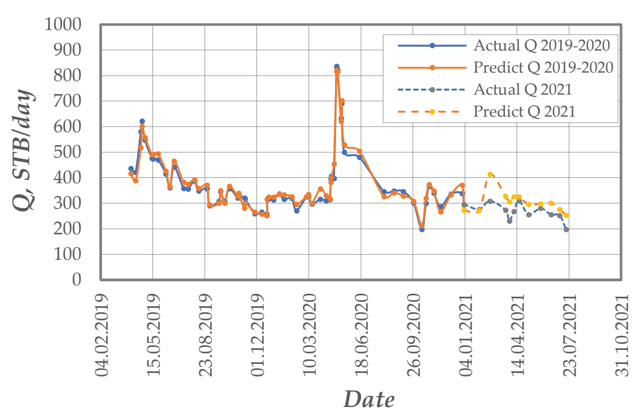

Fig. 5. Comparison between the results of the ANN model (predicted Q) and the actual test data (actual Q) of well HST5

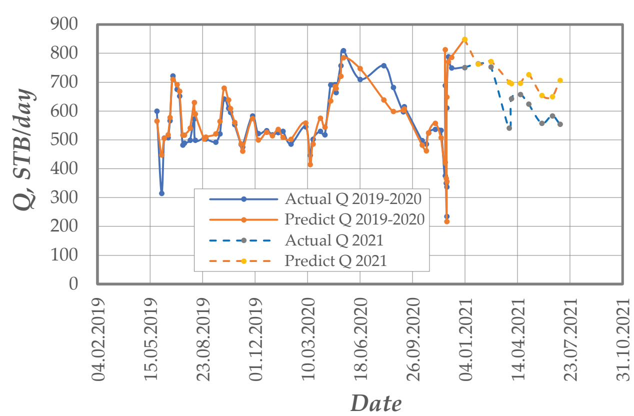

Fig. 6. Comparison between the results of the ANN model (predicted Q) and the actual test data (actual Q) well HST6

Conclusions

In this study, we addressed ANN method to predict oil production flow rate of gas lift for real data of HST Field. From the results obtained, it can be concluded that:

- The developed ANN model with a backpropagation algorithm including 8 neurons at the hidden layer gives flow rate prediction results with high accuracy compared to the reality (R^2=96% and a low RMSE of 32.612 bbl/d);
- The built ANN model not only accurately predicts the oil production flow rate of each well, but also accurately reflects the changing trend of the production flow rate over time. This proves that ANN model accurately represents the relationship between production parameters and flow rate. Therefore, the ANN model has been promised as an effective tool in production flow rate forecasting in oilfields;
- Forecasting the oil production flow rate at HST field is critical for monitoring the condition of the wells and developing timely intervention plans to maintain and ensure output. Furthermore, the ANN model also assists in determining reasonable production parameters to adjust flow, maintain output, and improve enhanced oil recovery;
- The authors propose changing the values of production parameters (choke size, gas injection rate, gas injection pressure…) at the same time to determine the optimal parameters to achieve desired flow rate within the range of values obtained from actual production data. These datasets are then fed back into the built ANN model. Production parameters are determined when the average production flow rate of the wells reaches the values set out.
- To enhance the precision of the ANN model, additional datasets from previous years, along with updated data, are required for further training.

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References

1. Tangren, R. F., Dodge, C. H., Seifert, H. S. (1949). Compressibility effects in two-phase flow. *Journal of Applied Physics*, 20(7), 637-645.

2. Gilbert, W. E. (1954). Flowing and gas-lift well performance. *API Drilling Production Practice*, 13, 126-157.

3. Achong, I. B. (1961). Revised bean performance formula for lake Maracaibo wells. *Shell Internal Report.*

4. Baxendell, P. B. (1958). Producing wells on casing flow-an analysis of flowing pressure gradients. Petroleum Transactions, 213, 202-206.

5. Ros, N. C. J. (1960). An analysis of critical simultaneous gas/liquid flow through a restriction and its application to flow metering. *Applied Scientific Research*, 9, 374-389.

6. Al-Attar, H. H., Abdul-Majeed, G. H. (1988). Revised bean performance equation for East Baghdad oil wells. *SPE Production Engineering*, 3, 127-131.

7. Al-Attar, H. H. (2008). Performance of wellhead chokes during subcritical flow of gas condensates. *Journal of Petroleum Science and Engineering*, 60(3-4), 205-212.

8. Beiranvand, M. S., Mohammadmoradi, P., Aminshahidy, B., et al. (2012). New multiphase choke correlations for a high flow rate Iranian oil field. *Mechanical Sciences*, 3(1), 43-47.

9. Espinoza, R. (2015, September). In digital oil field powered with new empirical equations for oil rate prediction. SPE-176750-MS. In: *SPE Middle East Intelligent Oil and Gas Conference and Exhibition. Society of Petroleum Engineers.*

10. Ghorbani, H., Wood, D. A., Moghadasi, J., et al. (2018). Predicting liquid flow-rate performance through wellhead chokes with genetic and solver optimizers: an oil field case study. *Journal of Petroleum Exploration and Production Technology*, 9(3), 1-19.

11. Gorjaei, R. G., Songolzadeh, R., Torkaman, M., et al. (2015). A novel PSO-LSSVM model for predicting liquid rate of two-phase flow through wellhead chokes. *Journal of Natural Gas Science & Engineering*, 24, 228-237.

12. AlAjmi, M. D., Alarifi, S. A., Mahsoon, A. H. (2015, March). In improving multiphase choke performance prediction and well production test validation using artificial intelligence: a new milestone. SPE-173394-MS. In: *SPE Digital Energy Conference and Exhibition. Society of Petroleum Engineers.*

13. Choubineh, A., Ghorbani, H., Wood, D. A., et al. (2017). Improved predictions of wellhead choke liquid critical-flow rates: Modelling based on hybrid neural network training learning-based optimization. *Fuel*, 207, 547-560.

14. Khan, M. R., Tariq, Z., Abdulraheem, A. (2018, April). In utilizing state of the art computational intelligence to estimate oil flow rate in artificial lift wells. SPE-192321-MS. In: *SPE Kingdom of Saudi Arabia Annual Technical Symposium and Exhibition. Society of Petroleum Engineers.*

15. Barjouei, H.S., Ghorbani, H., Mohamadian, N., Wood, D.A., Davoodi, S., Moghadasi, J., Saberi, H. (2021). Prediction performance advantages of deep machine learning algorithms for two-phase flow rates through wellhead chokes. *Journal of Petroleum Exploration and Production Technology*, 11, 1233-1261.

16. Ibrahim, A. F., Al-Dhaif, R., Elkatatny, S., Al Shehri, D. (2021). Applications of artificial intelligence to predict oil rate for high gas-oil ratio and water-cut wells. *ACS Omega*, 6(30), 19484-19493.

17. Azim, R. A. (2022). A new correlation for calculating wellhead oil flow rate using artificial neural network. *Artificial Intelligence in Geosciences*, 3, 1-7.

18. Somorotin, A. V., Martyushev, D. A., Stepanenko, I. B. (2023) Application of machine learning methods to forecast the rate of horizontal wells. *SOCAR Proceedings*, SI1, 70-77.

19. Kaleem, W., Tewari, S., Fogat, M., Martyushev, D. A. (2023) A hybrid machine learning approach based study of production forecasting and factors influencing the multiphase flow through surface chokes. *Petroleum*, In Press. https://doi.org/10.1016/j.petlm.2023.06.001

20. Tran, D. T., Le, T. H., Tran, X. Q., et al. (2020). Application of machine learning algorithm to forecast production for fracture basement formation, central arch, Bach Ho field. *PetroVietnam Journal*, 12, 37-46.

21. Nguyen, V. H., Le, P. N. (2019). Development of production prediction models for oil and gas wells. *PetroVietnam Journal*, 8, 14-20.

22. Tran, D. T., Dinh, D. H, Tran, X. Q., et al. (2019) Research on applied logistic growth model to forecast production for Lower Miocene, Bach Ho field. *PetroVietnam Journal*, 9, 16-22.

23. Marfo, S. A., Kporxah, C. (2020). Predicting oil production flow rate using artificial neural network and decline curve analytical methods. In: *Proceedings of 6th UMaT Biennial International Mining and Mineral Conference. Tarkwa, Ghana.*

24. Tripathy, S. S., Saxena, R. K., Gupta, P. K. (2013). Comparison of statistical methods for outlier detection in proficiency testing data on analysis of lead in aqueous solution. *American Journal of Theoretical and Applied Statistics*, 2(6), 233-242.

Прогнозирование дебитов добывающих скважин с использованием искусственной нейронной сети – на примере месторождения HST

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Реферат

Прогнозирование дебита нефти является важнейшим аспектом операций по добыче углеводородов. В настоящее время, прогнозирование дебита часто оценивается по теоретическим или эмпирическим моделям. Однако, теоретические и эмпирические модели имеют ограничения. В этом исследовании применяется искусственная нейронная сеть (ИНС) для прогнозирования дебита скважин. Было рассмотрено 256 наборов данных, собранных из шести скважин на месторождении HST Кыулонгского бассейна. Прогнозируемые результаты, полученные с помощью модели ИНС с восемью нейронами и алгоритмом обратного распространения ошибки, достигли высокой предсказуемости с высоким коэффициентом корреляции 0.964 и низким среднеквадратическим значением 32.612 баррелей в сутки. Таким образом, разработанные модели ИНС могут стать эффективным инструментом прогнозирования дебита добычи на нефтяных месторождениях.

Ключевые слова: искусственная нейронная сеть; алгоритм обратного распространения ошибки; прогнозирование дебита; метод многомерной регрессии; газлифт.

Süni neyron şəbəkəsindən istifadə edərək hasilat quyularının debitlərinin proqnozlaşdırılması – HST yatağının nümunəsində

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Xülasə

Neft debitinin proqnozlaşdırılması karbohidrogen hasilatı əməliyyatlarının ən vacib aspektidir. Hal-hazırda, debit proqnozu çox vaxt nəzəri və ya empirik modellərlə qiymətləndirilir. Lakin nəzəri və empirik modellərin məhdudiyyətləri var. Bu tədqiqatda quyuların debitini proqnozlaşdırmaq üçün süni neyron şəbəkəsi (SNŞ) tətbiq olunur. Kıulong hövzəsinin HST yatağındakı altı quyudan toplanan 256 məlumat dəsti nəzərdən keçirilmişdir. Səkkiz neyron və səhvin əks yayılması alqoritmi olan SNŞ modeli ilə əldə edilən proqnozlaşdırılan nəticələr yüksək korrelyasiya əmsalı 0.964 və aşağı orta kvadratik qiyməti günə 32.612 barel olan yüksək proqnozlaşdırmaya nail olmuşdur. Beləliklə, işlənmiş SNŞ modelləri neft yataqlarında debitin proqnozlaşdırılması üçün effektiv vasitə ola bilər.

Açar sözlər: süni neyron şəbəkəsi; səhvin geriyə yayılması alqoritmi; debitin proqnozlaşdırılması; çoxölçülü reqressiya metodu; qazlift.