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Application of Neural Network-Particle Swarm Modeling for Predicting Wellhead Choke Performance in the Niger Delta

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Abstract: *An accurate prediction of production rate for wellhead choke is highly vital in petroleum production engineering applications. It is very useful in the management of the life cycle of a well. Although, there are techniques in literature to predict wellhead choke performance for the Niger Delta fields; however, most of these techniques are empirical correlations derived from few datasets. Again, the nonlinear relationships that exist between liquid production rate and other several surface production parameters question the validity of existing empirical correlations. Thus, this study presents a new robust and soft-computing approach that was developed using the MATLAB software. To forecast the oil production rate of chokes for Niger Delta oil wells, this technique integrates the artificial neural network with the particle swamp optimization algorithm (ANN-PSO). Furthermore, the hybrid ANN-PSO model was trained and validated using 1595 production data points from seven (7) fields in the Niger Delta area. Different neural network architectures were evaluated, and the finest design was chosen. The new ANN-PSO model predicted the choke production rate with a training accuracy of average percentage error (APE) of 12.2 % and coefficient of determination (R2) of 0.8318. In addition, the new ANN-PSO model predicted the choke production rate with a testing accuracy of average percentage error (APE) of -9.2% and coefficient of determination (R2) of 0.9566. To determine the validity and accuracy of the new ANN-PSO model, the test data results of the new hybrid model, conventional ANN model and selected existing correlations were compared. The results suggest that the new ANN-PSO present a better choice for the estimation of liquid production rate with minimum error and acceptable accuracy than the ANN model and other published choke empirical correlations. Consequently, the hybrid model could be used for real-time prognosis of liquid production rate through wellhead choke.*

Keywords: *Artificial Neural Network (ANN), Algorithm, MATLAB, Particle Swarm Optimization (PSO), Wellhead Choke Performance Modeling.*

1. Introduction

Estimating individual well performance, optimizing and improving well and reservoir productivity requires an understanding of fluid flow principles. An oil and gas production system simply involves the transportation of subsurface reservoir fluid to the surface, processes and treats the fluid, stores and transfer the fluid to a buyer who then sells to the consumers.

Wellhead choke has remained an integral component in regulating the production rate of an oil and gas well by restricting flow through the choke box before entering the flowline. The primary objective of installing a choke is to enable control over fluid flow rates, however regulating flow through chokes also eliminate numerous possible production and reservoir challenges such as sand production, water and gas coning, formation damage, stabilizing flow rate (Guo *et al.*, 2007). Other functions include protecting surface equipment from downstream pressure surges, reduction of high wellhead flowing pressures, or sustaining economical production rate limits set by the regulatory authorities.

Since oil production rate is extremely sensitive to changes in the choke size, modeling flow through chokes is vitally important for oil production simulation. In fact, choke performance model contributes to the accuracy of well performance prediction as well as full system nodal analysis. Several empirical correlations based on experimental and field data have been developed by the researchers to determine liquid flow rate as a function of GLR, wellhead flowing pressure, and choke size. Furthermore, the multiphase flow rate across wellhead chokes is an important metric in evaluating reservoir performance and long-term viability. Fluid flowrates must be precisely monitored and predicted to determine production volume and resource recovery, as well as to build a consistent and expected pattern of flow in producing wells.

Chokes can be used to regulate flowrate either at the wellhead or downhole. Fixed and variable wellhead chokes are the two basic types, each with various capabilities depending on material compositions and configuration. When two phase flow is carried via wellhead chokes, either a critical flow or a subcritical flow can occur.

Critical flow is achieved as the fluid velocity gets to sonic velocity, which happens when the ratio of downstream pressure to upstream pressure is less than 0.588 (Ghareeb and Shedid, 2007) while Subcritical flow condition occurs when the mass flow of the fluid is less than the sonic velocity.

Figure 1 shows the performance of a wellhead choke under critical and subcritical flow.

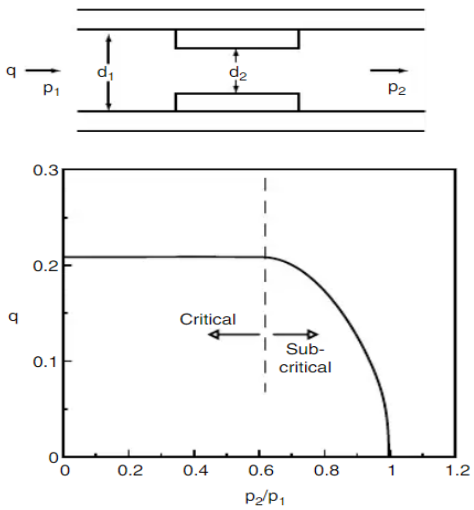

Figure1. *A typical choke performance curve (Guo et al., 2007)*

Where.

P_1 = Upstream pressure of choke or wellhead pressure, psi

P_2 = Downstream pressure of choke or flowline pressure, psi

q = flow rate, bbl/d

$d_{1=\text{Upstream pipe diamter,in}}$

$d_{2=\text{Choke diamter,in}}$

As standard oil practice, the evaluation of choke performance should be done under critical or sonic flow (Mesallati *et al.,* 2000). Stable well production and separation condition is enabled by sonic flow (Guo *et al.*, 2007). Consequently, downstream-to-upstream pressure ratio determines the existence of critical flow. Clegg (2007) maintained that for this condition to happen, the downstream pressure must be approximately 0.55 or less of the upstream pressure. Sadiq (2012) opined that under critical flow conditions, the flow rate is a function of the upstream pressure.

Due to the complexities and inconsistency of field data several correlations have been published to predict the flow of multiphase fluid through wellhead chokes. The validity of these developed correlations is bound to the region in which they were developed, and are dependent on insufficient ranges of flow variable. For Niger Delta region limited works have been done on wellhead choke performance. Owolabi *et al.*, (1991) and Okon *et al.*, (2015) are the works in the public domain and they are based on few data points from Niger Delta region making them less flexible for good performance prediction and the entire nodal analysis.

Okon et al. (2015) used a neural network with the standard back propagation (BP) model, widely known as the BPNN, to determine choke performance in Niger Delta fields. If the initial set of weights is not adequately specified, the BP model's gradient descent search strategy is likely to becoming bound in local optimal solutions. In certain situations, the computations may even surpass or deviate from the optimum. Due to the general BPNN's constraints, research teams have looked beyond the present model for more robust optimization approaches that can help attain the optimum answer in an effective manner. The search for such robust techniques led to the use of evolutionary algorithm for the optimization of neural networks.

To improve the performance of the predictions a novel approach would be used in the study to solve the complex and nonlinear problem associated with these data culminating from the Niger delta fields. A neural network trained with particle swamp optimization algorithm will be used to optimize the performance predictions of wellhead chokes. This training algorithm was chosen because it is easy to implement, converges faster and has good stability.

This study is to develop computational intelligence model for the prediction of multiphase flow performance of Niger Delta oil wells.

2. Materials and Methods

2.1. Data Collection and Analysis

The computational hybrid-models developed and validated in this study are based on a total of 1595 production and test data collected from seven (7) oil producing fields in Niger Delta Fields with input variables of choke size, wellhead pressure, flowline pressure, basic sediment and water, gas-liquid ratio, gas-oil ratio, fluid temperature, oil gravity and output variable as liquid critical-flow rate. A classification was made based on P_2/P_1 ratio to screen critical from subcritical data sets.

2.2. Data Preparation

For this work, the following data sets used represent all the wells flowing under critical condition. The parameters used with the statistical analysis are shown in the **Table 1**.

Table1. *Statistical analysis for the parameters used in the Critical flow model.*

Parameters	Units	Min	Mean	Max	Standard Deviation
Choke size	(*/64th inch)	12	37	68	11
Wellhead pressure	P si	95	470	1780	275
BS&W	%	0	39.2	97	31.3
Gas-Liquid Ratio(GLR)	SCF/STB	5	698	9732	894
Gas-Oil Ratio(GOR)	SCF/STB	4	1582	20316	2346
Fluid Temperature	O F	60	94	187	14
Oil gravity	^{o} API	0.809	0.8957	0.9471	0.0347
Net Oil rate	STB/D	30	939	3500	701
Gross Oil Rate	STB/D	208	1511	3504	709

2.3. Models Description

The data sets were divided into 1495 data points for training and 100 data points for testing. A feed forward network with one input layer, two hidden layers, one output layer and back propagation training algorithm was used for the ANN model development while a feed forward network with one input layer, two hidden layers, one output layer and particle swamp optimization training algorithm was used for both ANN-PSO model development respectively. Eight (8) inputs variables and one output variable have been used for the developed models. The input parameters are the basic surface well parameters listed in the Table 3 with adding one transformation term $\frac{T}{T_{sc}}$

Table2. *Input and output parameters for critical flow ANN-PSO model*

Input	Output
Choke size (*/64th inch)	Net Oil rate (STB/D)
Wellhead pressure (P si)	
BS&W (%)	
Fluid Temperature(O F)	
Gas-Liquid Ratio(SCF/STB)	
Gas-Oil Ratio(SCF/STB)	
Oil gravity (^{o} API)	
$\frac{T}{T_{sc}}$	

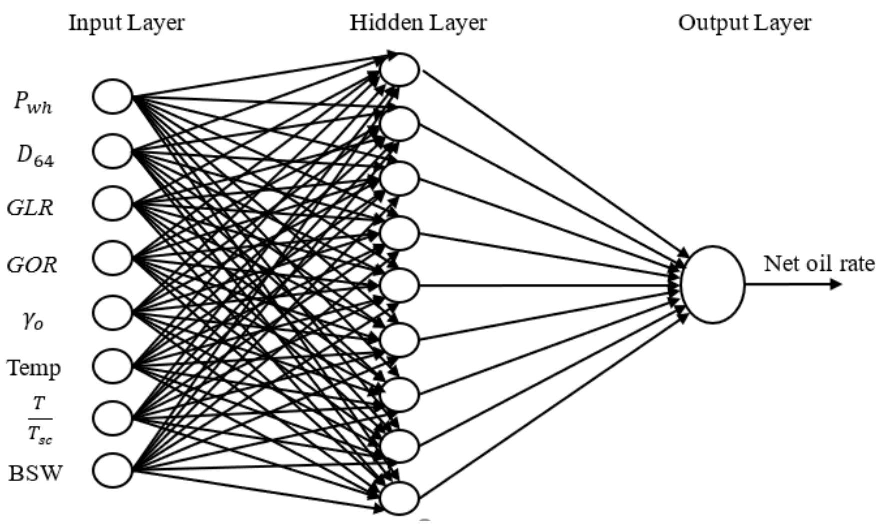

Figure2. *A single layered Feed-Forward Neural Network architecture.*

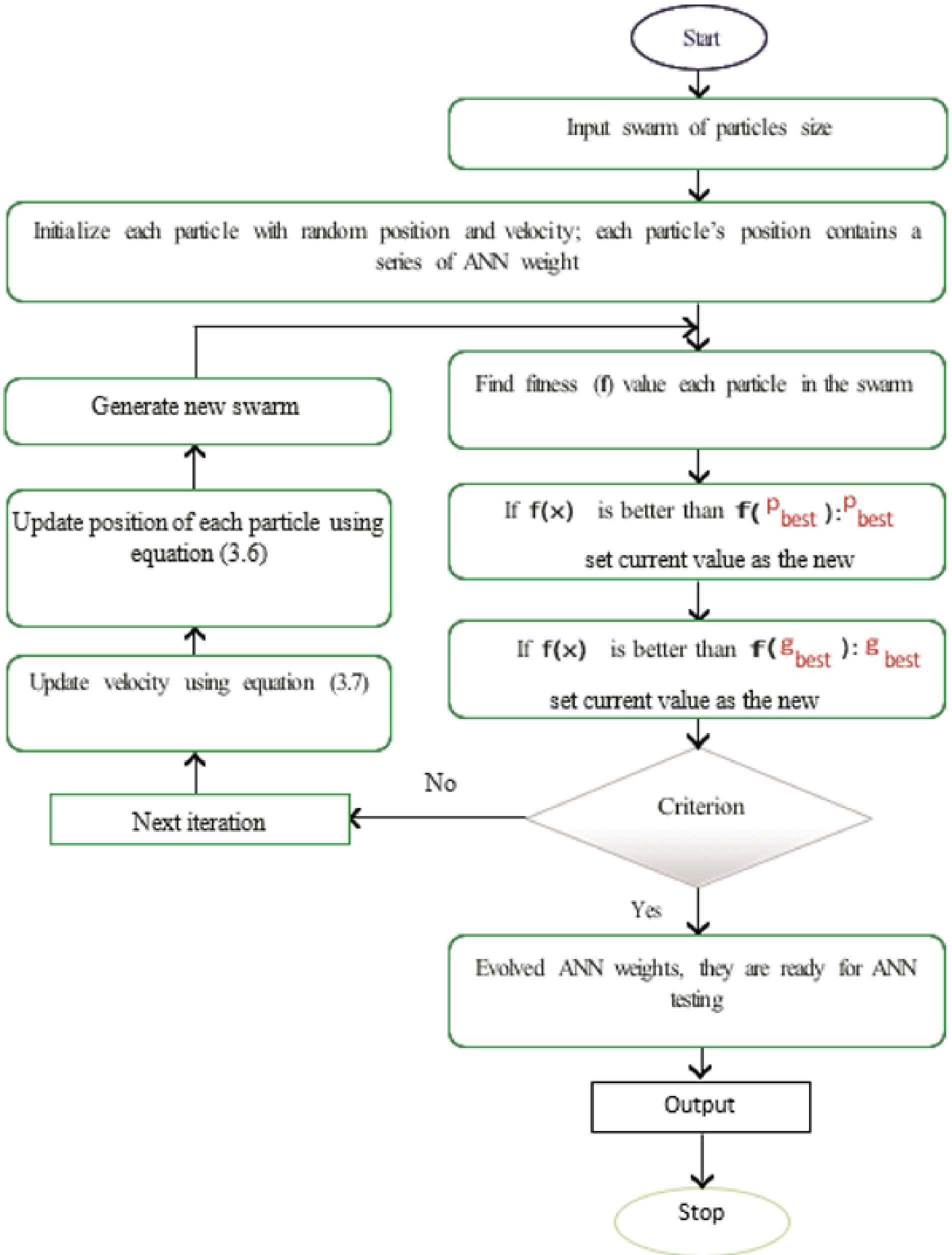

Figure3. *Flow diagram for the ANN-PSO program developed (Mohammad, 2014)*

2.4. Models Evaluation Criteria

To demonstrate the accuracy and robustness of the developed computational model, the predicted wellhead choke performance prediction (Liquid critical flowrate) predictions was compared with the actual field data, conventional ANN model and other existing correlations statistically.

3. Results and Discussion

A total of 1595 data points were randomly split into two sets with a ratio of 1495:100 data points. The 1495 data points were used to train the models, while the remaining 100 data points were utilized to assess the trained models' prediction skills.

During training, ANN model predicted Net Oil Rate with RMSE of 249 and R2 of 0.8774 as shown in **Table 3** and **Figure 4** while the hybrid ANN-PSO predicted Net Oil Rate with the RMSE of 291 and R^2 of 0.8318 as shown in **Table 3** and **Figure 5**. In addition, a set of 100 data points was used to assess the generalization performance and consistency of the trained Model. ANN predicted Net Oil Rate with RMSE of 147 and R^2 of 0.9292 as shown in **Table 4** and **Figure 6**, and ANN-PSO predicted Net Oil Rate with RMSE of 116 and R^2 of 0.9566 as shown in **Table 4** and **Figure 7**.

Table3. *Statistical analysis of ANN-PSO and ANN Models for the Training Dataset*

Models	Statistical Error Metrics				
	R2	APE	AAPE	MSE	RMSE
ANN-PSO	0.8318	12.2	35.83	84945	291
ANN	0.8774	7.64	28.44	61932	249

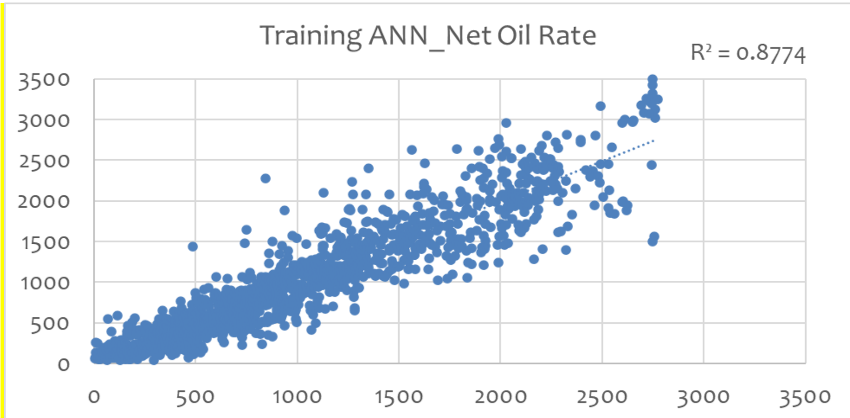

Figure4. *Plot of Actual field Values against ANN Model Predicted Values for Training Data set*

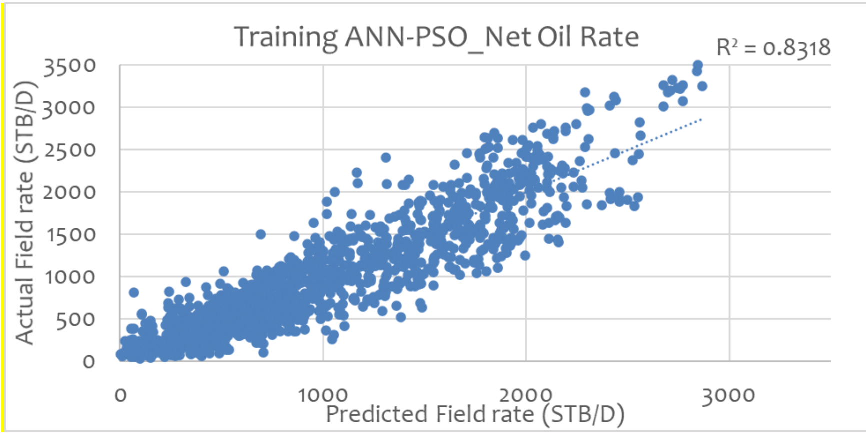

Figure5. *Plot of Actual Field Values Against ANN-PSO Model Predicted Values for Training Data Set*

Table4. *Statistical analysis of ANN-PSO and ANN Models for the Testing Dataset*

Models	Statistical Error Metrics				
	R2	APE	AAPE	MSE	RMSE
ANN-PSO	0.9566	9.2	20.6	13391	116
ANN	0.9292	12.5	23	21655	147

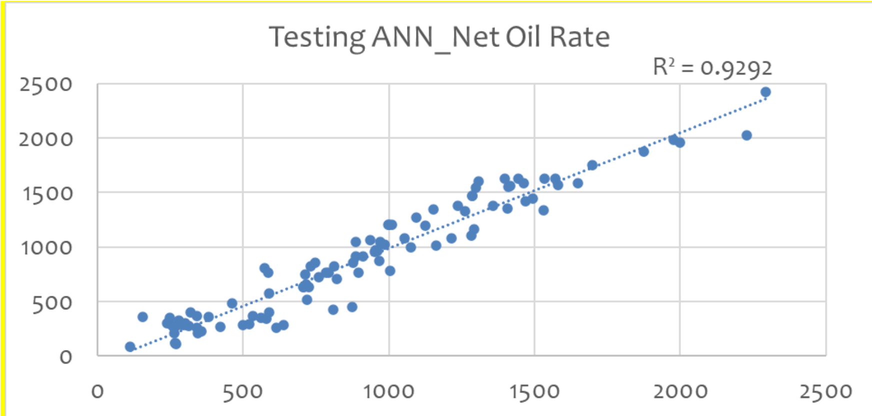

Figure6. *Plot of Actual field Values against ANN Model Predicted Values for Testing Data Set.*

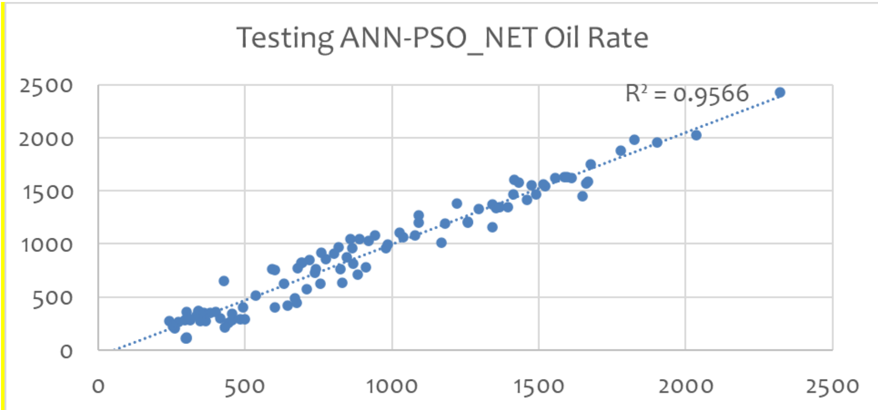

Figure7. *Plot of Actual field Values against ANN-PSO Model predicted Values for Testing Data Set.*

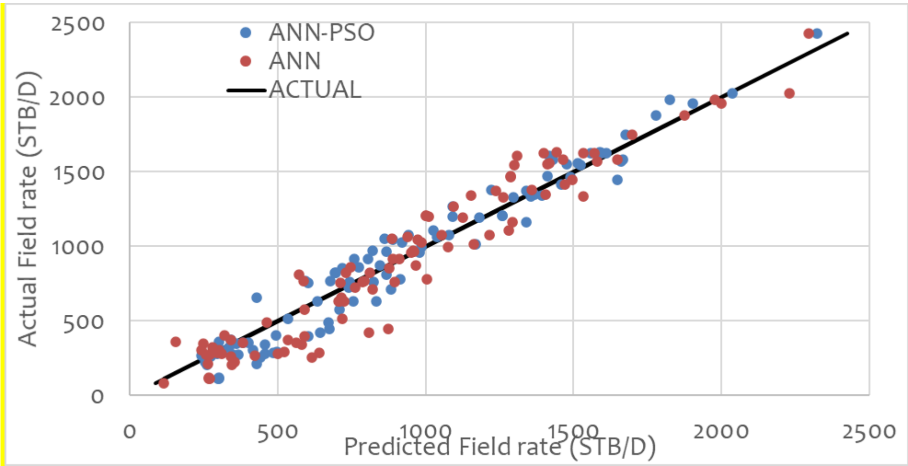

Figure8. *Comparison Plot of Actual Field Values With ANN-PSO and ANN Models Predicted Values for Testing Data Set.*

Both models can predict most of the actual field rate closely. However, the ANN-PSO model showed a more acceptable performance that is closer to the actual value than the ANN model.

When the performance of the two models, ANN-PSO and ANN, was compared during training, the ANN-PSO model predicted Net Oil Rate with a slightly higher AAPE than ordinary ANN, while PSO-ANN produced R^2 of 0.8318, which was less than the R^2 produced by ordinary ANN, which was 0.8774; this was due to overfitting by the ANN model. PSO-ANN outperformed ANN in testing unseen data, yielding a lower AAPE and higher R^2.

3.1. Comparison of ANN-PSO Performance with Exiting Models

In this section, the performance and accuracy of some existing empirical correlations for predicting wellhead choke performance was analyzed statistically with the testing dataset and result was compared with the performance of the developed ANN-PSO model. **Table 5** shows the ANN-PSO model comparison with existing empirical correlation using statistical metrics of R^2, AAPE and RMSE.

Table 5: ANN-PSO Model Comparison with Existing Empirical Correlation

Models	Statistical Error Metrics				
	R2	APE	AAPE	MSE	RMSE
ANN-PSO	0.9566	9.2	20.6	13391	116
ANN	0.9292	12.5	23	21655	147
Gilbert (1954)	0.5531	-0.5	42.9	506934	712
Baxendell (1958)	0.5575	-22.5	47.6	928805	964
Achong(1961)	0.4375	-47.7	67.6	2403578	1550
Ros (1960)	0.6203	-10.6	41	558972	748
Beiranvandi et al., (2012)	0.5168	-4.7	52.5	851880	923
Okon et al., (2015)	0.599	-30.6	44.8	817976	904
Owolabi et al., (1991)	0.8451	3.4	25	91844	303

From a visual comparison of **Table 5**, the overall accuracy and performance of ANN-PSO over all considered existing empirical correlations performance as shown by a higher R^2 value and lesser AAPE and RMSE values, proves the ANN-PSO model better performance.

4. Conclusions

The successful implementation of the hybrid (ANN-PSO) model in the Niger Delta region have proved worthwhile in choke performance prediction by providing a better data-driven solution to the problem of modeling the non-linear relationship of surface production rate parameters, a common challenge for existing empirical correlations.

The soft computing approach have also proved to be time and cost effective by providing an alternative in terms of eliminating regular flow disturbance when conducting maximum efficiency rate (MER) test.

The performance of this model can be further improved by larger data set from various fields in the Niger Delta.

References

[1] Abbas, K., Habib, R., Hojjat, R., & Seyed, M. (2015). Application of Artificial Neural Network-Particle Swarm Optimization Algorithm for Prediction of Asphaltene Precipitation During Gas Injection Process. Journal of Energy Resources Technology, 137 (6), 062904.

[2] Abdolhossein, H., Mohammad-Hossein, G., Shahab, A., & Mohsen, M. (2016). Accurate determination of the CO2-crude oil minimum miscibility pressure of pure and impure CO2 streams: A robust modelling approach. The Canadian Journal of Chemical Engineering, 94(2), 253-261.

[3] Abdul-Majeed, G. (1988). Correlations Developed to Predict Two Phase Flow Through Wellhead Chokes. Retrieved from https ://doi.org/10.2118/88-39-26.

[4] Achong, I. (1961). Revised Bean and Performance Formula for Lake Maracaibo wells. Internal co. report, Shell Oil Co., Houston, TX.

[5] Al-Ajmi, M., Alarifi, S., & Mahsoon, A. (2015). Improving Multiphase Choke Performance Prediction and Well Production Test Validation Using Artificial Intelligence: A New Milestone. In: SPE digital energy conference and exhibition. The Woodlands. Retrieved from https ://doi.org/10.2118/17339 4MS.

[6] Alfredo, G., & Richard, S. (2003). Improved Neural-Network Model Predicts Dewpoint Pressure of Retrograde Gases. Journal of Petroleum Science and Engineering, 37(3-4), 183-194. doi:10.1016/S0920-4105(02)00352-2

[7] Ashford, F. (1974). An Evaluation of Critical Multiphase Flow Performance Through wellhead chokes. Journal of Petroleum Technology, 26(8), 843–850. Retrieved from https ://doi.org/10.2118/4541-PA.

[8] Baxendell, P. B. (1958). Producing Wells on Casing Flow – An Analysis of flowing pressure gradients. AIME.

[9] Beiranvand, M., Mohammadmoradi, P., Aminshahidy, B., Fazelabdolabadi, B., & Aghahoseini, S. (2012). New multiphase choke correlations for a high flow rate Iranian oil field. 3(1), 43–47. Retrieved from https://doi.org/10.5194/ms-3-43-2012

[10] Choubineh A, Ghorbani H, Wood DA, Moosavi SR, Khalafi E, Sadatshojaei E. (2017). Improved Predictions of Wellhead Choke Liquid Critical-Flow Rates: Modeling Based on Hybrid Neural Network Training Learning Based Optimization. Fuel 207, 547–560.

[11] Eberhart, R., & Kennedy, J. (1995). A New Optimizer Using Particle Swarm Theory. Proceedings of the Sixth International Symposium on Micro Machine and Human Science, (pp. 39-43). Nagoya, Japan.

[12] Elgibaly, A., & Nashawi, I. (1998). New Correlations for Critical and Subcritical Two-phase Flow Through Wellhead Chokes. Journal of Canadian Petroleum Technology, 37(6).

[13] Feng, H. (2006). Self-generation RBFNs Using Evolutional PSO Learning. Neurocomputing, 70, 241-251.

[14] Ghareeb, M., & Shedid, A. (2007). A new correlation for calculating wellhead production considering influences of temperature, GOR and water-cut for artificially lifted wells. International Petroleum Technology Conference. Dubai, U.A.E.

[15] Ghorbani, H., J., M., & Wood, D. (2017). Prediction of Gas Flowrates from Gas Condensate Reservoirs Through Wellhead Chokes Using A Firefly Optimization Algorithm. J Nat Gas Sci Eng, 43, 256–271. Retrieved from https ://doi.org/10.1016/j.jngse .2017.04.034.

[16] Gilbert, W. (1954). Flowing and Gas-Lift Well Performance. In Drilling and production practice. American Petroleum Institute.

[17] Guo, B., Lyons, W., & Ghalambor. (2007). Petroleum Production Engineering: A computer-assisted approach. Elsevier Science and Technology Books.

[18] Habib, R., & Abbas, K. (2014). A New Support Vector Machine and Artificial Neural Networks for Prediction of Stuck Pipe in Drilling of Oil Fields. Journal of Energy Resources Technology, 136(2), 024502.

[19] Haykin, S. (2009). Neural networks and learning machines. (3rd, Ed.) Pearson Prentice Hall.

[20] Kennedy, J. (2006). Swarm Intelligence. In A. Y. Zomaya (Ed.), Handbook of Nature-Inspired and Innovative Computing: Integrating Classical Models with Emerging Technologies 187-219). Secaucaus, New Jersey, US: Springer.

[21] Kennedy, J., Eberhart, R., & Shi, Y. (2001). Swarm Intelligence. San Francisco: Morgan Kaufmann.

[22] Kexi, L., Quanke, Y., Xia, W., & Wenlong, J. (2012). A Numerical Corrosion Rate Prediction Method for Direct Assessment of Wet Gas Gathering Pipelines Internal Corrosion. Energies, 5(10), 3892-3907. doi: https://doi.org/10.3390/en5103892

[23] Mesallati, A., Biznati, M., & Mansouri. (2000). Multiphase-Flow Choke Correlations for Offshore Bouri Oil field. International Gas Union 21st World Gas Conference, (p. 49). Nice, France.

[24] Mohaghegh, S., & Ameri, S. (1995). Artificial Neural Network as a Valuable tool for Petroleum Engineers. Society of Petroleum Engineers, 1-2.

[25] Networks, Kennedy, J., & Eberhart, R. (1995). Particle Swarm Optimization. in: Proceedings of IEEE International Conference on Neural, (1942-1948). Perth, Australia.

[26] Okon, A., Udoh, F., & Appah, D. (2015). Empirical Wellhead Pressure - Production Rate Correlations for Niger Delta oil wells. Society of Petroleum Engineers, SPE Paper 178303.

[27] Osman, E., Abdel-Wahhab, O., & Al-Marhoun, M. (2001). Prediction of Oil PVT Properties Using Neural Networks. Society of Petroleum Engineers, SPE Paper, 68233.

[28] Owolabi, O., Dune, K., & Ajienka, J. (1991). Producing the Multiphase Flow Performance through Wellhead Chokes for the Niger Delta oil wells. International Conference of the Society of Petroleum Engineers Nigeria Section Annual Proceeding.

[29] Pilehvari, A. (1981). Experimental Study of Critical Two-Phase Flow through Wellhead chokes. University of Tulsa, Tulsa.

[30] Poli, R. (2008). Analysis of the Publications on the Applications of Particle Swarm Optimisation. Journal of Artificial Evolution and Applications, 10 pages.

[31] Ros, N. C. (1961). An Analysis of Critical Simultaneous Gas/Liquid Flow through a Restriction and Its Application to Flow metering. Applied Science Research, 9(1), 374–389. Retrieved from https ://doi.org/10.1007/BF003 82215.

[32] Saqid, D. (2012). Prediction of Oil Flow Rate through Choke at Critical Flow for Iraqi Oil Wells. Journal of Petroleum Resources and Studies, 212(6), 53-79.

[33] Shamisi, & Maitha, H. (2013). Using MATLAB to develop Artificial Neural Network for predictong Solar Radiation in Al Ain City. United Arab Emirates University, Al Ain City.

[34] Tarek, A.-A. G., & Hrairi, M. (2018). A New Choke Correlation to Predict Flow Rate of Artificially Flowing Wells. Journal of Petroleum Science and Engineering. doi:doi: 10.1016/ j.petrol.2018.08.004.

[35] Tariq, Z., Mohamed, M., & Abdulazeez, A. (2019). Real-time prognosis of Flowing Bottom-Hole Pressure in a Vertical Well for A Multiphase Flow Using Computational Intelligence Techniques. Journal of Petroleum Exploration and Production Technology, 1-18.

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