

Research Article

Improved Mechanistic and Intelligent Models for Bottom-Hole Pressure from Vertical Oil Wellhead Data

Oluwatoyin Akinsete^{*} , Blessing Adesiji 

Department of Petroleum Engineering, University of Ibadan, Ibadan, Nigeria

Abstract

In the Petroleum industry, pressure losses in tubing installations must be determined accurately. Traditionally, flowing bottom-hole pressure was determined using mechanical down-hole gauges, this procedure is not cost-effective and less efficient as mechanical tools are prone to damage. This research aims to compare an improved mechanistic model of pressure determination with a machine-learning model that predicted bottom-hole pressure readings. Guo's mechanistic model was modified in this study while considering some assumptions that affect the estimation. A pressure gradient expression was obtained, and it was solved using a piece-wise iteration approach. The machine learning model was based on an Artificial Neural Network algorithm to predict and further improve the accuracy of the prediction while considering a large production dataset from different wells of the field. In developing the model, the initial dataset was pre-processed to about 2,500 data points; the model was trained, tested, and cross-validated based on the parameters from the data. The results obtained from the mechanistic model gave an accuracy of 0.888 when tested on a fraction of the Volve dataset, while the Artificial Neural Network model gave an accuracy of 0.999 on the test dataset. Finally, this shows that, apart from the ability of machine learning to handle large datasets, it also predicted a high value of accuracy when compared to the improved mechanistic model.

Keywords

Bottom-hole Pressure, Intelligent Models, Mechanistic Model, Multiphase Flow, Vertical Oil Well

1. Introduction

The pressure exerted by a static fluid depends only upon the depth of the fluid, the density of the fluid, and the acceleration of gravity, and this applies to the pressure exerted by flowing fluid downhole. In the Oil and Gas Industry, it is a difficult process to determine the bottom-hole pressure directly using down-hole gauges [1-3], due to the redundancy of the gauges. Cost effective mechanistic correlations for predicting bottom-hole pressure is preferred in the industry [3, 4]. The most commonly used mechanistic models are that of Kabir and Hasan [5]; Ansari et al. [6]; Chokshi et al. [7]; Gomez et al. [8]

and Guo [9]. According to (Gomez et al. [10] and Okorie et al. [3], mechanistic models are mostly considered to be dependable and appropriate as they incorporate flow-relevant parameters. Nevertheless, mechanistic models accuracy are constrained by copious assumptions and their intricate nature [11]. Also, the predicting ability and applicability of these past mechanistic correlations is a concern in the industry, hence, the need to develop an improved mechanistic model for BHP determination that will be more accurate and reliable.

Also, technological advances led to drilling complex wells

^{*}Corresponding author: oalolakunle@gmail.com (Akinsete Oluwatoyin Olakunle)



which pose more difficulty in accounting for bottom-hole pressure prediction. There is a strong need to process large real-time data sets obtained from the Well and estimate instantaneous flowing bottom-hole pressure, machine learning models have presented an integrated approach to overcoming the restrictions posed by developed correlations in terms of handling a wide variety of data sets. Numerous Tubing Performance Relation (TPR) models have been developed for analyzing multiphase flow in vertical pipes. The TPR models for multiphase flow wells fall into two categories: Homogeneous flow and separated flow models. Homogeneous models treat multiphase as a homogeneous mixture and do not consider the effects of the liquid holdup (no slip assumptions). The major advantage of these models comes from their mechanistic nature. They can handle gas-oil-water three-phase and gas-oil-water-sand four-phase systems. It is easy to code these mechanistic models in computer programs. Separated flow, on the other hand, is more realistic than the homogenous-flow models. They are usually given in the form of empirical correlations. They consider the effect of flow regimes and liquid hold (slip). The major disadvantage of the separated flow models is that it is difficult to code them in computer programs because most correlations are presented in graphic form [12]. A model for predicting Bottom-hole Pressure (BHP) based on easily obtainable wellhead parameter has been the preferred method in the oil and gas industry.

Given the numerous downsides of using mechanistic models, the following researchers: Ashena and Moghadasi [13]; Akinsete and Isehunwa [14]; Awad [15]; Di et al. [16]; Tariq et al. [17]; Olamigoke and Onyeali [18]; Okoro et al. [19]; Goliatt et al. [20]; Nwanwe et al. [21]; Jin et al. [22], have deployed the utilized different intelligent models algorithm, such as artificial neural networks, support vector machines, hybrid intelligent systems, fuzzy systems etc., to monitor BHP in the oil and gas industry. These models was reported by Okorie et al. [3] in 2025 to have achieved varying degrees of success in the prediction of bottom-hole pressure. Though many of these intelligent models have been stated to exhibit superior predictive performance compared to mechanistic and empirical models [3], but they have not been explicitly presented for BHP estimation.

The objective of this study is described below;

- 1) To develop a correlation for the prediction of BHP by modifying original Guo's model. Guo's method involves the solution of a general energy equation-derived model using Newton-Raphson's Numerical algorithm for the hydraulic and friction pressure at depth. The BHP is obtained from definite integrals with limits interval between wellhead pressure and bottom-hole pressure in the estimations of frictional pressure. This research aims to solve numerically using a piece-wise iteration in wellbore segment lengths to further increase the accuracy.
- 2) To develop a machine learning algorithm that predicts the bottom-hole pressure from wellhead data. This will

be achieved by building an Artificial Neural Networks model that takes Wellhead data as input data and predicts the bottom-hole pressure as output data. The algorithm will be trained with a real dataset from an Oil field named Equinor in Norway and tested with a fraction of the same Production information. Other intelligent models would also be tested in this research such as Support Vector Machines, Gradient Boosting, etc.

- 3) To do a comparative study of the developed mechanistic model with other empirical correlations in bottom-hole flowing pressure determination.
- 4) To do a comparative study of the developed mechanistic model correlation with the most accurate machine learning model.

Many approaches have been developed to fully understand the multiphase flow in wells, from the principle of linear momentum and the conservation of mass, pressure gradient equation was developed. In the Petroleum Industry, both experimental and theoretical methods have been used to get insights on correlations that govern multiphase flow.

The complexity of inhomogeneous multiphase flow presented a great challenge for early researchers, investigations then originated from curve fittings to equations using experimental or field data. The methods can be classified as empirical correlations and mechanistic models.

To handle a large variety of data sets at a certain condition, the developed correlations are not fully capable to perform such a task. One of the many problems faced by developers is the selection of the most suitable correlation for a particular condition. A more integrated approach was introduced by the application of Machine learning Algorithms, with Artificial Neural Networks being the most common algorithm applied to solve the above problem, better Bottom-Hole pressure can be predicted given the right data sets.

In 1952 Poettmann and Carpenter [23] developed a correlation from the energy equation and data information from 34 flowing oil wells and 15 gas-lift wells using tubing diameters of 2, 2½, and 3½ inches. The correlation was developed using production GLR of about 5,000 SCF/bbl of total liquid; total liquid production rates from 60 to 1,500 STB/D; production WOR's of about 56STB/STB; Oil gravities range between 30 to 54° API, and well depth to 11,000ft. With no attempt to determine the liquid hold-up factor, the work focused on oil. Water and gas as a single phase. The friction factor of multiphase flow was correlated with the product of the inside diameter of the tubing and the mass velocity of the mixture flowing through the pipe [24]. This model made the assumption that the total output flow rate was used to calculate the density at any one pressure point.

Baxendell and Thomas [25] in 1961 worked on Poettmann and Carpenter correlation after discovering that the model failed to extrapolate from low flow rates to high flow rates as the method proved inapplicable to high flow rate conditions. They suggested some modifications to the model to fit perfectly to the high-rate correlation derived from Shell de Ven-

ezuela's La Paz field in Venezuela. Series of experiments were carried out at rates up to 5,000 B/D. The work revealed a relationship between energy-loss factor and mass flow rate, it is applicable to wide-range of conduit sizes and fluid types at a high flow rate.

The Significance of high flow rates was justified for practical purposes. An accuracy of 5% was achieved with the right PVT data for both vertical and horizontal flow.

In 2001 Guo Boyun [9] demonstrated that a mechanistic model that was originally developed for modeling gas, water, oil and solid in a borehole drilling can be used to determine inflow performance relationship of Oil wells in the absence of bottom-hole pressure, he derived a model and solved it using Newton-Raphson numerical procedure for the hydraulic and friction pressure at depth. An integral summation between limits of wellhead pressure and flowing bottom-hole pressure was done to arrive at the numerical solution. The model's accuracy was accepted within practical error limits after testing with data for high GOR wells and low GOR wells.

This present study is an extension of Guo's base model for flowing bottom-hole pressure estimation. The modifications made for the extension are;

- 1) Consider a homogenous flow that is mechanistic in nature, and can handle gas-oil-water-sand four phase system.
- 2) The use of bottom-hole temperature rather than an average tubing temperature.
- 3) Flow is steady and Isothermal; no work was done by the gas flow.

Osman et al. [26] in 2005 presented an Artificial Neural Network (ANN) for predicting flowing bottom-hole pressure and consequently the pressure drop in multiphase flow. The model considered 206 field data sets after data pre-processing which reduced 386 data sets from Middle East fields to what was used in the model development. The datasets were divided into training, validation and testing sets. To develop the model and tune the network weights, the training sets were used; the validation set is used to monitor the generalization of the developed network, and to examine the final performance of the developed model. Osman et al's model achieved a correlation coefficient of 0.9735, the maximum absolute relative error of 7.1401% and average absolute percent error of 2.1654%. The research demonstrated the use of an Artificial Neural Network model in providing solutions to multiphase flow problems.

Also, Jahanandish [27] in 2011 presented an Artificial Neural Network model for predicting bottom-hole flowing pressure and as a result the pressure drop in vertical multiphase flowing wells. After considering a wide range of data sets, 413 field data sets collected from the research work, the model outperformed the conventional models with 0.9222 correlation coefficient and 3.5% absolute average percent error. The above statistical results were derived from implementing a feed-forward neural networks hidden layer in the predictive model. Akinsete and Isehunwa [14] in 2013 de-

veloped a model for estimating bottom-hole pressure in condensate wells while considering the liquid hold up. The approach originated from the general energy balance equation. A generalized expression for calculating flowing bottom-hole pressure was developed, flowing bottom-hole pressures in dry and condensate gas wells can be calculated using the derived expression. From the study, it was shown that the pressure profiles in condensate wells differ from dry wells as higher pressure drops are obtained in condensate wells. The significance of liquid holdup consideration was highlighted, zero hold-up assumption can affect the accuracy of the prediction model.

Recent improvements in pressure prediction techniques revealed that most of the mechanistic models failed to provide the desired accuracy, and major adjustments are still needed. Machine learning models have been of great help in this area of research as recent developers can boast of the desired accuracy in their work. The most common prediction model used to solve difficult engineering problems is Artificial Neural Networks as they have been widely accepted in the Petroleum Industry. There are other prediction tools that can be incorporated in this research such as Support Vector Machines, Gradient boosting algorithms, etc. Large datasets are acquired in each area of Petroleum Industry which makes the applicability of Artificial Neural Networks techniques worthwhile. In multiphase flow prediction, researchers have successfully used the technique in prediction as explained below.

In 2014, Li and Jennifer [24] presented a combined approach involving a calculation procedure using multiphase correlation and Artificial Neural Network models. Back Propagation neural network models were incorporated into a piece-wise calculation approach of determining pressure gradient, this resulted in higher prediction accuracy. The model gave the lowest average absolute percent error to be 3.1%. Comparing to the multiphase correlations, the final combined approach has an average absolute percent error of 23.0%. The model was however published with a user interface bottom-hole pressure calculator deployed.

2. Materials and Methods

The model that was developed in this research is of two forms, the mechanistic model and machine learning model.

2.1. Mechanistic Model Development

From the law of conservation of energy which can be used in the analysis of flowing fluids, the behavior of fluids can be described qualitatively. The law states that the energy of a fluid entering a section of the tubing, in addition to the work done on the fluids in the two sections with negative energy losses in the sections is equal to the energy of the fluid at the output section. Static pressure gradient, friction pressure gradient, and kinetic pressure gradient all make up the energy

equation.

This research work owns its basis to this energy; hence, the equation was derived from first principles to obtain the equation (1)

$$\frac{dP}{dZ} = \rho_m + \frac{\rho v dv}{g_c dZ} + \frac{f \rho_m v^2}{2 g_c d} \quad (1)$$

Solid:

$$W_s = 7.22 \times 10^{-4} Q_s \gamma_s \frac{lb}{sec} \quad (2)$$

Liquid:

$$W_l = 4.0554 \times 10^{-3} (Q_o \gamma_o + Q_w \gamma_w) \frac{lb}{sec} \quad (3)$$

Gas:

$$W_g = 8.667 \times 10^{-7} Q_g \gamma_g \frac{lb}{sec} \quad (4)$$

A final density mixture equation is obtained from the weight function of each component, is expressed below:

$$\rho_m = \frac{(7.22 \times 10^{-4} Q_s \gamma_s) + (4.0554 \times 10^{-3} (Q_o \gamma_o + Q_w \gamma_w)) + (8.667 \times 10^{-7} Q_g \gamma_g)}{(1.157 \times 10^{-5}) Q_s + (6.499 \times 10^{-5} (Q_o + Q_w)) + \frac{4.7115 \times 10^{-5} Q_g T}{P}} \quad (5)$$

Then the velocity mixture can be obtained as expressed below:

$$v_m = \frac{6.785 \times 10^{-3} Q_g T}{AP} + \frac{9.359 \times 10^{-3} (Q_o + Q_w)}{A} \quad (6)$$

Substituting all the equations into equation (1), a pressure gradient equation (7) is obtained as:

$$\frac{dP}{dZ} = \frac{\frac{P}{Q_g T} [15.32 Q_s \gamma_s + 86.07 (Q_o \gamma_o + Q_w \gamma_w) + 0.0184 Q_g \gamma_g]}{\frac{P}{Q_g T} [0.25 Q_s + 1.38 (Q_o + Q_w)] + 1} \left[1 + \frac{f \left(\frac{6.785 \times 10^{-3} Q_g T + 9.359 \times 10^{-3} P (Q_o + Q_w)}{A} \right)^2}{2 g_c d} \right] \quad (7)$$

From Beggs and Brill's procedures [28] for calculating pressure traverses, iterating on length increment was explained and pressure increment was also highlighted as means of solving the dP/dZ over any pressure or length increment. The understanding of the piece-wise calculation originated from this procedure, the Beggs and Brill length incremental procedure is explained below:

- 1) Determine the Initial pressure
- 2) Estimate change in length,
- 3) Calculate fluid properties and average pressure and temperature,

The above equation (1) represents the general equation for characterizing pressure drop associated with fluid flow, which is the foundation of the mechanistic model. Considering the flow of each component of the fluid in the equations (2-6) below:

- 4) Determine calculated dP/dZ ,
- 5) Determine the change in length from calculated pressure gradient,
- 6) Compare the estimated results and calculated values,
- 7) Repeat the procedure until the error between calculated and estimated values are close

Under normal conditions, the bottom-hole pressure is calculated from the wellhead parameters, by estimating the pressure gradient along the wellbore. However, it seems impracticable to determine the pressure gradient of the multi-phase system and multiply with the Well length to obtain the

bottom-hole pressure. This gives large prediction errors in the developed model.

A new approach is used to provide a solution to the pressure gradient expression derived above (equation 7). The method is a piece-wise calculation which takes wellhead parameters, then proceed to determine the average gradient value for each partitioned segment till the bottom of the wellbore is reached (Figure 1).

The iteration commenced using an initial pressure which is the wellhead pressure, using the developed correlation, dP/dZ was calculated, and the iteration then proceeds to obtain a new pressure based on the convergence conditions. In selecting the convergence condition, the depth of the well was used to obtain the length of each segment. This step-by-step method that moves from the wellhead to bottom-hole, aims to reduce errors when compared to the partitions used in this case. This might seem like a tedious process, but the computation was carried out using a program written in python programming language.

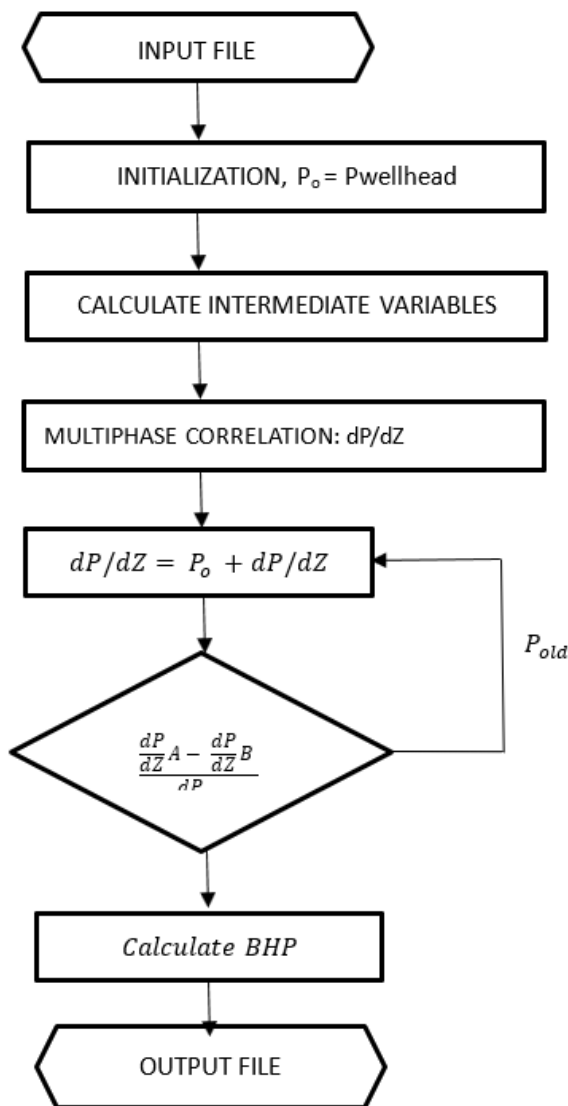


Figure 1. BHP Piece-wise Computation from WHP.

2.2. Machine Learning Model

A large dataset which was obtained from a production field in XYZ Continental Shelf in Norway. Initially, it contained about 15,000 data points, and it was reduced to about 2,500 data points after pre-processing of removing null values, outliers, and duplicates. The dataset was then divided into training and testing using a ratio of 70: 30 respectively, before fitting using an Artificial Neural Network. The Artificial Neural Network (ANN) was used to predict the flowing bottom-hole pressure in this research, the model is Multi-layer Perceptron Regressor (MLP), which is a supervised learning algorithm that learns a function $f(\cdot): R^m \rightarrow R^o$ by training on the dataset, where m is the number of input dimension and o is the number of output dimensions. For the features of datasets $X = X_1, X_2, \dots, X_9$ and target variable y , which is a non-linear function approximator for the regression problem (Figure 2).

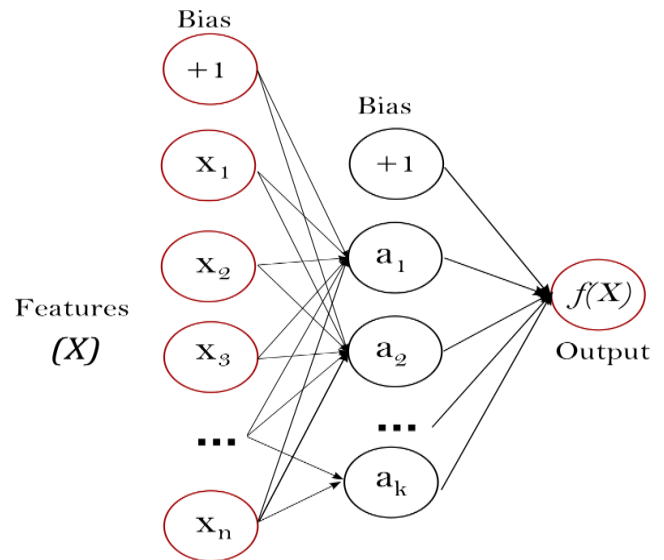


Figure 2. Hidden Layer MLP.

The input layer (X) is to the left side of the figure above, it consists of a set of neurons $X_i \parallel \{X_1, X_2, \dots, X_9\}$ representing the input features values from the previous layer is transformed by each neuron in the hidden layer with the weighted linear summation (equation 8), followed by a

$$f(x, w) = \phi(x, w) = \phi\left(\sum_{i=1}^n (X_i, W_i)\right) \quad (8)$$

non-linear activation function $g(\cdot): R^m \rightarrow R^o$. In this case the, non-linear activation function is the rectified linear unit function (Relu). Finally, the last hidden layer gives values to the output layer to transform them into output values.

Where: Φ is an activation function (Relu), W is a matrix of weights, X is a matrix of inputs (features). The aim is to obtain the weights of the equation, such that the mean absolute error

is very close to zero. To do this non-linear activation function was used to solve, through the following step:

Weight Updates

The general rule of weight updates is the delta rule:

New weight = old weight - Derivative Rate * learning rate

The learning rate is introduced as a constant (usually very small), in order to force the weight to get updated very smoothly and slowly (to avoid big steps and chaotic behavior).

In order to validate this equation:

- 1) If the derivative rate is positive, it means that an increase in weight will increase the error, thus the new weight should be smaller.
- 2) If the derivative rate is negative, it means that an in-

crease in weight will decrease the error, thus there is a need to increase the weights.

- 3) If the derivative is 0, it means that we are in a stable minimum. Thus, no update on the weights is needed, meaning we reached a stable state.

Iteration Process

Since the weights are updated with a small delta step at a time, it will take several iterations in order to learn. The iterative procedure is necessary for the optimization and is usually done using the Limited memory Broyden-Fletcher-Goldfarb-Shanno Solver. The final weight matrixes were optimized to obtain an effective weight that can model as the equation used to obtain the bottom-hole pressure.

$$f(x, w) = \phi(x, w) = \phi\left(\sum_{i=1}^n (X_i, W_i)\right) = \max(0, X_s) \quad (9)$$

Other algorithms like Support Vector Machines (SVM), Decision Trees (DT), and Random Forest (RF) were also used.

3. Results

A pressure-depth profile diagram was used in the visualization, the mechanistic model predicted value and the measured value are plotted on the same graph (Figure 3). After completing the model training and testing with a certain por-

tion of the datasets, the obtained predicted results were compared with the actual measured readings from the field (Table 1). In a bid to validate the predicting power of the ANN model, the results were compared with other intelligent models of Support Vector Machines (SVM), Decision Trees (DT), and Random Forest (RF). Table 2 showed the results of the statistical metrics (Coefficient of Determination (COD), Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE)) used.

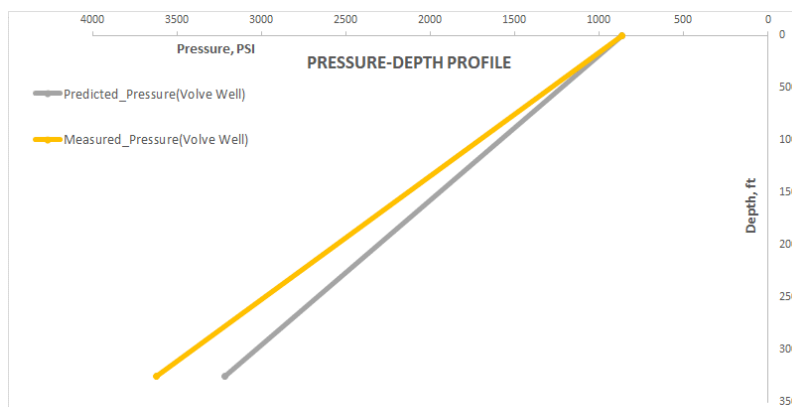


Figure 3. Pressure-Depth Profile.

Table 1. ANN Model compared with other Intelligent Models.

Measured BHP	Intelligent Models Computed BHP			
	ANN	SVM	DT	RF
212.332	212.364	216.199	212.741	212.826
202.878	202.897	202.978	202.878	206.557

Measured BHP	Intelligent Models Computed BHP			
	ANN	SVM	DT	RF
200.246	200.254	200.346	200.246	200.300
199.805	199.813	203.552	200.246	200.300
196.028	196.061	196.128	196.028	201.993
197.894	197.899	217.977	195.306	197.087
198.465	198.462	213.992	200.246	198.865
202.469	202.468	202.569	202.469	204.637

Table 2. Accuracy of ANN compared with other Intelligent Models.

Machine Learning Algorithm	COD	MAE	RMSE
ANN	0.999972	0.026574	0.074051
SVM	0.802163	7.228097	11.599087
DT	0.996661	0.601207	1.506820
RF	0.997053	0.525837	1.415665



Figure 4. Pair Plot distribution of all the variables.

4. Discussion

From the above Table 1, the BHP predicted by the developed mechanistic model and the measured BHP value gave

average absolute percent relative error range of 0.073 – 0.440 revealing that the high accuracy of the developed mechanistic model in predicting BHP.

It was observed from Tables 2 and 3 that amongst all intelligent models used (ANN, Support Vector Machines, Decision Trees, Random Forest), the ANN Model performed better

in predicting BHP with a Coefficient of Determination of 0.999972, Root Mean Squared Error of 0.074051 and Mean Absolute Error of 0.026574. These showed a great prediction ability of ANN as all the data points lie on the line of best fit with reduced errors.

Pair Plots distribution (Figure 4) builds on two basic figures,

the histogram and the scatter plot. The histogram on the diagonal allows us to see the distribution of a single variable while the scatter plots on the upper and lower triangles show the relationship (or lack thereof) between two variables. The distribution of all the features as seen above is along the diagonal and relationships can be seen outside the diagonal to both left and right.

5. Conclusions

This work showed the development of new mechanistic and intelligent models capable of accurately predicting Bottom-hole Pressure in the absence of experimental data. The ANN model significantly outperformed all the other intelligent models.

Acknowledgments

The authors acknowledge the Department of Petroleum Engineering, University of Ibadan, Nigeria where this research work was carried out.

Author Contributions

Oluwatoyin Akinsete: Conceptualization, Supervision, Validation, Writing – review & editing

Blessing Adesiji: Data curation, Formal Analysis, Methodology, Writing – original draft.

Funding

This work is not supported by any external funding.

Data Availability Statement

The data supporting the outcome of this research work has been reported in this manuscript.

Conflicts of Interest

The authors declare no conflicts of interest.

References

- [1] Spesivtser, P., Sinkov, I., Zimina, A., Umnov, A., Yarullin, R., Vetrov, D. Predictive model of bottomhole pressure based on machine learning. *Journal of Petroleum Science and Engineering*. 2018, 166, 825-841. <https://doi.org/10.1016/j.petrol.2018.03.046>
- [2] Alrumah, M., Aladwani, F., Alatefi, S. Toward the development of a universal choke correlation-global optimization and rigorous computational techniques. *Journal of Engineering Research*. 2020, 8(3), 240-254. <https://doi.org/10.36909/jer.v8i3.7717>
- [3] Okorie, E. A., Saad, A., Ahmad, A., Raja, R. S. Modelling the flowing bottom hole pressure of oil and gas wells using multivariate adaptive regression splines. *Journal of Petroleum Exploration and Production Technology*. 2025, 15, 22. <https://doi.org/10.1007/s13202-025-01933-9>
- [4] Baki, S., Dursun, S. Flowing Bottomhole Pressure Prediction with Machine Learning Algorithms for Horizontal Wells. In *Proceedings of the SPE-ATCE, Houston, Texas, USA, 2022*. <https://doi.org/10.2118/210235-MS>
- [5] Kabir, C. S., Hasan, A. R. A Study of Multiphase Flow Behaviour in Vertical Oil Wells: Part II-Field Application. In *Proceedings of the SPE-California Regional Meeting, Oakland, California, USA, 1986*. <https://doi.org/10.2118/15139-MS>
- [6] Ansari, A. M., Sylvester, N. D., Sarica, C., Shoham, O., Brill, J. P. A comprehensive mechanistic model for upward two-phase flow in wellbores. *SPE Production and Facilities*. 1994, 9(02), 143-151. <https://doi.org/10.2118/20630-PA>
- [7] Chokshi, R. N., Schmidt, Z., Doty, D. R. Experimental Study and the Development of a Mechanistic Model for Two-Phase Flow through Vertical Tubing. In *Proceedings of the SPE Western Regional Meeting, Anchorage, Alaska, 1996*. <https://doi.org/10.2118/35676-MS>
- [8] Gomez, L. E., Shoham, O., Schmidt, Z., Chokshi, R. N., Brown, A., Northug, T. A Unified Mechanistic Model for Steady-State Two-Phase Flow in Wellbores and Pipelines. In *Proceedings of the SPE-ATCE, Houston, Texas, USA, 1999*. <https://doi.org/10.2118/56520-MS>
- [9] Guo, B. Use of Wellhead Pressure Data to Establish Well-Inflow Performance Relationship. In *Proceedings of the SPE-Eastern Regional Meeting, Canton, Ohio, USA, 2001*. <https://doi.org/10.2118/72372-MS>
- [10] Gomez, L. E., Shoham, O., Schmidt, Z., Chokshi, R. N., Northug, T. Unified Mechanistic Model for steady-state two-phase flow: horizontal to vertical upward flow. *SPE Journal*. 2000, 5(03), 339-350. <https://doi.org/10.2118/65705-PA>
- [11] Awadalla, M., Yousef, H., Al-Hinai, A., Al-Shidani, A. Prediction of oil well flowing bottom-hole pressure in petroleum fields. In *Proceeding of the International Conference on Industrial Engineering and Operations Management, Kuala Lumpur, Malaysia, 2016, 8-10*. https://icomsociety.org/icom_2016/pdfs/636.pdf

- [12] Guo, B., Lyons, W. C., Ghalambor, A. Petroleum Production Engineering. Lafayette: Elsevier Science & Technology Books, 2007, pp. 1-288.
- [13] Ashena, R., Moghadasi, J. Bottom hole pressure estimation using evolved neural networks by real coded ant colony optimization and genetic algorithm. Journal of Petroleum Science and Engineering. 2011, 77(3-4), 375-385. <https://doi.org/10.1016/j.petrol.2011.04.015>
- [14] Awad, M. A. M. Pressure drop in vertical multiphase flow using neuro fuzzy technique: a comparative approach. B. Eng. Thesis, Universiti Teknologi, PETRONAS, 2014.
- [15] Di, Q. F., Chen, W., Zhang, J. N., Wang, W. C., Chen, H. J. An Artificial Intelligence Prediction Method of Bottomhole Flowing Pressure for Gas Wells based on Support Vector Machine. Advances in Engineering Research. 2016, 105. <https://doi.org/10.2991/mme-16.2017.28>
- [16] Tariq, Z., Mahmoud, M., Abdulraheem, A. Real-time prognosis of flowing bottom-hole pressure in a vertical well for a multiphase flow using computational intelligence techniques. Journal of Exploration, Production and Technology. 2020, 10, 1411-1428. <https://doi.org/10.1007/s13202-019-0728-4>
- [17] Olamigoke, O., Onyeali, D. C. Machine learning prediction of bottomhole flowing pressure as a time series in the Volve field. International Journal of Frontiers in Engineering and Technology Research. 2022, 2022(0202), 020-029. <https://doi.org/10.53294/ijfetr.2022.2.2.0039>
- [18] Okoro, E. E., Sanni, S. E., Obomanu, T. Igbiniedion, P. Predicting the effect of selected reservoir petrophysical properties on bottom-hole pressure via three computational intelligence techniques. Petroleum Research. 2023, 8(1), 118-129. <http://doi.org/10.1016/j.ptirs.2022.07.001>
- [19] Goliatt, L., Mohammad, R. S., Abba, S. I., Yaseen, Z. M. Development of Hybrid Computational data-intelligence model for flowing bottom-hole pressure of oil wells: New strategy for oil reservoir management and monitoring. Fuel. 2023, 350, 1-13, <https://doi.org/10.1016/j.fuel.2023.128623>
- [20] Nwanwe, C. C., Duru, U. I., Anyadiegwu, C. Ekejuba, A. I. B. An artificial neural network visible mathematical model for real-time prediction of multiphase flowing bottom-hole pressure in wellbores. Petroleum Research. 2023, 8, 370-385. <https://doi.org/10.1016/j.ptirs.2022.10.004>
- [21] Jin, M., Emami-Meybodi, H. Ahmadi, M. Flowing Bottomhole Pressure during Gas Lift in Unconventional Oil Wells. In Proceedings of the SPE-ATCE, San Antonio, Texas, USA, 2023. <https://doi.org/10.2118/214832-MS>
- [22] Poettmann, F. H., Carpenter, P. G. The Multiphase flow of Gas, Oil and Water through Vertical Flow Strings with Application to the Design of Gas Lift Installations. Drilling and Production Practice. 1952, 257.
- [23] Li, X. M., Jennifer, H. B. A Combined Bottom-hole Pressure Calculation Procedure Using Multiphase Correlations and Artificial Neural Network Models. In Proceedings of the SPE-ATCE, Amsterdam, The Netherlands, 2014. <https://doi.org/10.2118/170683-MS>
- [24] Baxendell, P. B., Thomas, R. The Calculation of Pressure Gradients in High-Rate Flowing Wells. Journal of Petroleum Technology. 1961, 13. <https://doi.org/10.2118/2-PA>
- [25] Osman, E. A., Ayoub, M. A., Aggour, M. A. An Artificial Neural Network Model for Predicting Bottomhole Pressure in Vertical Multiphase Flow. In Proceedings of the SPE-Middle East Oil and Gas Show and Conference, Kingdom of Bahrain, 2005. <https://doi.org/10.2118/93632-MS>
- [26] Jahanandish, I., Salimifard, B., Jalalifar, H. Predicting bottomhole pressure in vertical multiphase flowing wells using artificial neural networks. Journal of Petroleum Science and Engineering. 2011, 75, 336-342. <https://doi.org/10.1016/j.petrol.2010.11.019>
- [27] Akinsete, O. O., Adesiji, B. A. Bottom-Hole Pressure Estimation from Wellhead Data using Artificial Neural Network. In Proceedings of the SPE-NAICE, Lagos, Nigeria, 2019. <https://doi.org/10.2118/198762-MS>
- [28] Beggs, D. H., Brill, J. P. A study of two-phase flow in inclined pipes. Journal of Petroleum Technology. 1973, 25(05), 607-617. <https://doi.org/10.2118/4007-PA>

Biography



Akinsete Oluwatoyin is an Associate Professor at University of Ibadan, Department of Petroleum Engineering. He completed his PhD in Petroleum Engineering from University of Ibadan in 2015, and his Master of Science in Petroleum Engineering from the same institution in 2001. Recognized for his exceptional contributions, Dr. Akinsete has been honored with the Professional Engineer designation by the esteemed Council for the Regulation of Engineering in Nigeria (COREN). He has participated in multiple international research collaboration projects in recent years.



Adesiji Blessing is a Developer Advocate. He had his Bachelor of Science in Petroleum Engineering from University of Ibadan in 2018. He previously worked as Developer Relations, Data Scientist, and AI Developer Engineer.

Research Field

Akinsete Oluwatoyin: Reservoir Engineering, Gas Engineering, Mathematical Modeling, Data Analytics.

Adesiji Blessing: Data Scientist, Coding, Artificial Intelligence Developer