SPE 93632

Artificial Neural Network Model for Predicting Bottomhole Flowing Pressure in Vertical Multiphase Flow

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This paper was prepared for presentation at the 14th SPE Middle East Oil & Gas Show and Conference held in Bahrain International Exhibition Centre, Bahrain, 12–15 March 2005.

Abstract

Accurate prediction of pressure drop in vertical multiphase flow is needed for effective design of tubing and optimum production strategies. Several correlations and mechanistic models have been developed since 1950. In addition to the limitations on the applicability of all existing correlations, they all fails to provide the desired accuracy of pressure drop predictions. The recently developed mechanistic models provided little improvements in pressure drop prediction over the empirical correlations. However, there is still a need to further improve the accuracy of prediction for a more effective and economical design of wells and better optimization of production operations.

This paper presents an Artificial Neural Network (ANN) model for prediction of the bottom-hole flowing pressure and consequently the pressure drop in vertical multiphase flow. The model was developed and tested using field data covering a wide range of variables. A total of 206 field data sets collected from Middle East fields; were used to develop the ANN model. These data sets were divided into training, cross validation and testing sets in the ratio of 3:1:1. The testing subset of data, which were not seen by the ANN model during the training phase, was used to test the prediction accuracy of the model and compare its performance against existing correlations and mechanistic models. The results showed that the present model significantly outperforms all existing methods and provides predictions with higher accuracy. This was verified in terms of highest correlation coefficient, lowest average absolute percent error, lowest standard deviation, lowest maximum error, and lowest root mean square error. A trend analysis was also conducted and showed that the present model provides the expected effects of the various physical parameters on pressure drop.

Introduction

A reliable and accurate way of predicting pressure drop in vertical multiphase flow is essential for the proper design of well completions and artificial-lift systems and for optimization and accurate forecast of production performance. Because of the complexity of multiphase flow, mostly empirical or semi-empirical correlations have been developed for prediction of pressure drop.

Numerous correlations have been developed since the early 1940s. Most of these correlations were developed under laboratory conditions and are, consequently, inaccurate when scaled-up to oil field conditions[1]. The most commonly used correlations are those of (Hagedorn and Brown[2]; Duns and Ros[3]; Orkiszewski[4]; Beggs and Brill[5]; Aziz and Govier[6]; Mukherjee and Brill correlation[7]). Numerous studies were done to evaluate and study the applicability of those correlations under different ranges of data[8-15]. Most researchers agreed upon the fact that no single correlation was found to be applicable over all ranges of variables with suitable accuracy[1]. It was found that correlations are basically statistically derived, global expressions with limited physical considerations, and thus do not render them to a true physical optimization.

Mechanistic models are semi-empirical models used to predict multiphase flow characteristics such as liquid hold up, mixture density, and flow patterns. Based on sound theoretical approach, most of these mechanistic models were generated to outperform the existing empirical correlations. The most widely used mechanistic models are those of Hasan and Kabir[16]; Ansari *et al*[17].; Chokshi *et al*.[18]; Gomez *et al*.[19]. Other studies were conducted to evaluate the validity of such mechanistic models[20-22]. Generally, each of these mechanistic models has an outstanding performance in specific flow pattern prediction and that is made the adoption for certain model of specific flow pattern by investigators to compare and yield different, advanced and capable mechanistic models.

However, a statistical study indicated that there is no pronounced advantage for mechanistic models over the current empirical correlations in pressure prediction ability when fallacious values are excluded[1].

The recent development and success of applying artificial neural networks (ANN) to solve various difficult engineering problems has drawn the attention to its potential applications in the petroleum industry. The use of artificial intelligence in petroleum industry can be tracked back just almost twenty years[23]. The use Artificial Neural Network (ANN) in solving many petroleum industry problems was reported in the literature by several authors. Recently, ANN has been applied in the multiphase flow area and achieved promising results compared to the conventional methods (correlations and mechanistic models). With regard to this field, a few researchers applied ANN technique to resolve some problems associated with multiphase problems including pressure drop[24-25], flow patterns identification[26-27], liquid hold up[30], and gas and liquid superficial velocities[28].

Experience showed that empirical correlations and mechanistic models failed to provide a satisfactorily and a reliable tool for estimating pressure in multiphase flow wells. High errors are usually associated with these models and correlations. Artificial neural networks gained wide popularity in solving difficult and complex problems, especially in petroleum engineering.

The artificial intelligence (AI) or soft computing shows better performance over the conventional solutions. AI's aim can be stated as "the development of paradigms or algorithms that require machines to perform tasks that apparently require cognition when performed by humans[29]. Artificial intelligence techniques are classified into ANN, genetic algorithms, expert systems, and fuzzy logic. ANN is a machine that is designed to model the way in which the brain performs a particular task or function of interest. The system of ANN has received different definitions[30]. However, a widely accepted term is that adopted by Alexander and Morton[31]: "A neural network is a massively parallel distributed processor that has a natural propensity for storing experiential knowledge and making it available for use".

This paper presents an Artificial Neural Network (ANN) model for prediction of the bottom-hole flowing pressure and consequently the pressure drop in vertical multiphase flow. The model was developed and tested using field data covering a wide range of variables. A total of 206 field data sets collected from Middle East fields; were used to develop the ANN model. These data sets were divided into training, cross validation and testing sets in the ratio of 3:1:1. The testing subset of data, which were not seen by the ANN model during the training phase, was used to test the prediction accuracy of the model and compare its performance against existing correlations and mechanistic models.

Model Development

The developed ANN model utilizes multiple-layer feed forward networks, which were selected due to their capabilities of representing non-linear functional mappings between inputs and outputs. The developed model consists of one input layer (containing nine input neurons or nodes), which represent the input parameters (oil rate, water rate, gas rate, diameter of the pipe, length of pipe, wellhead pressure, oil gravity "API", surface temperature, and bottomhole temperature), three hidden layers (the first one contains six nodes, the second and third hidden layer each contains three nodes) and one output layer (contains one node) which is bottomhole pressure. This topology is achieved after a series of optimization processes by monitoring the performance of the network until the best network structure was accomplished (Fig. 1).

Data Acquisition and Pre-processing

A total of 386 data sets were collected from different Middle East fields. The data used for developing the model covers an oil rate from 280 to 19618 BPD, water cut up to 44.8%, and gas oil ratios up to 675.5 SCF/STB. To check the validity of the collected data and remove the suspected outliers, empirical correlations and mechanistic models were used to predict the bottomhole flowing pressures and compare it with the measured value. The mechanistic models of Hasan and Kabir[16], Ansari *et al.*[17], Chokshi *et al.*[18], Gomez *et al.*[19], and the correlations of Hagedorn and Brown[2], Duns and Ros[3], Orkiszewski[4], Beggs and Brill[5], and Mukherjee and Brill[7] were used. Data sets which consistently resulted in poor predictions by all correlations and mechanistic models were considered to be invalid and, therefore, removed. A cut-off-error percentage (relative error) of 15% was implemented for the whole data. After such a screening, a total 206 data sets were used to develop the artificial neural network model. These were *randomly* divided into three different groups: training, validation, and testing. The *training set* is used to develop and adjust the weights in a network; the *validation set* is used to ensure the generalization of the developed network during the training phase, and the *testing set* is used to examine the final performance of the network and compare the model performance with other correlations and mechanistic models. Different partitioning ratios were tested (2:1:1, 3:1:1, and 4:1:1). The ratio of 4:1:1 (suggested by Haykin[30]) yielded better training and testing results. Table 1 shows the statistical analysis of the used data.

Results and Discussion

To evaluate a newly developed model, two tests must be performed. First, the model must be tested to prove that it is stable and simulates the physical process; this is done through "trend analysis". Second, the predictive performance of the new model must be compared against existing correlations and models. This is done through cross plots and a group error analysis, using the average absolute percent error as an indicator..

Trend Analysis

A trend analysis was carried out to check whether the developed model is physically correct or not. For this purpose, synthetic sets were prepared where in each set only one input parameter was changed while other parameters were kept constant. To test the developed model, the effects of gas rate, oil rate, water rate, tubing diameter, and pipe length on flowing bottomhole pressure were determined. Figures 2 and 3 show the effect of gas rate and tubing diameter on bottomhole pressure, respectively. The developed model showed the correct trend where the flowing bottomhole pressure decreases as the gas rate and tubing diameter increase.

Some correlations and Gomez model showed a decrease in bottomhole pressure followed by an increase when gas rate increase. The reason is that when the gas liquid ratio becomes very high, additional increase in gas rate results in an increase in frictional and acceleration pressure drop which is more than the decrease in the hydrostatic head. Figures 4 through 6 show the effect of water rate, oil rate, and depth, respectively. The figures show that the present model successfully produced the expected trends; i.e. the bottomhole pressure is increasing with increase in water rate, oil rate, and depth.

Comparison of the ANN Model against Other Models

As mentioned earlier, 41 data sets were used to evaluate the predictive capability of the present artificial neural network model and compare its performance against existing correlations and mechanistic models. The prediction performances of five correlations that have been used by the industry (Hagedorn and Brown[2]; Duns and Ros[3]; Orkiszewski[4]; Beggs and Brill[5]; Mukherjee and Brill[7]), and four mechanistic models (Hasan and Kabir[16]; Ansari *et al*[17].; Chokshi *et al.*[18]; Gomez *et al.*[19]) were compared against the present model. Table 2 lists the important statistical parameters (defined in Appendix A) for comparative evaluation of the correlations, mechanistic models and the present ANN model.

To demonstrate the robustness of the developed model, the group error analysis was conducted. Average absolute percent (E_a) relative error is used as a good indicator of the accuracy. This effective comparison of all investigated correlations and mechanistic models provides a good means of evaluating models performance. AAPE is utilized in this analysis by grouping input parameter and hence plotting the corresponding values of average absolute relative error for each set. Figures 7 through 11 present the statistical accuracy of flowing bottomhole pressure correlations and models for different groups of the studied parameters. These include oil rate, gas rate, water rate, tubing diameter and depth, respectively. The figures showed that the present model consistently outperformed all correlations and mechanistic models and resulted in the lowest average absolute relative error in all data ranges of the studied parameters.

Cross plots were used to compare the performance of the developed mode and other correlations and mechanistic models. A 45° straight line between the estimated versus actual data points is drawn on the cross plot, which denotes a perfect correlation line. The scattered cloud of data points indicates bad correlation. Figures 12 through 21 present cross plots of predicted versus measured bottomhole pressure actual for the developed model, other empirical correlations and mechanistic models. Investigation of these figures clearly shows that the developed ANN model outperforms all correlations and mechanistic models.

Several observations and conclusions can be made by investigation of Figures 12 to 21 and Table 2. Hasan and Kabir model produced the largest error in predicting the bottomhole flowing pressure (E_a of 9.23% and correlation coefficient of 0.7502). Accuracy of prediction was improved for Ansari et al. model (E_a of 6.75% and correlation coefficient of 0.8178). The other two mechanistic models of Chokshi et al. and Gomez et al. resulted in a similar performance. Surprisingly, the empirical correlations, except for Duns and Ros, performed much better than the mechanistic models. Finally, Mukherjee and Brill correlations outperformed other correlations and mechanistic models (E_a of 4.903% and correlation coefficient of 0.8792). The predicted pressure drop by the present ANN model is compared against the measured values in Figure 21. Investigation of the figure clearly demonstrates the outstanding performance of the present model. The model predicted the 41 values of bottomhole flowing pressure with E_a of 2.165% compared to 9.23% for Hasan and Kabir. The correlation coefficient for the model is 0.9735 compared to 0.9015 for Orkiszewski, and 0.8836 for Chokshi model.

Conclusions

1. Artificial Neural Network model based back-propagation learning algorithm has been used was developed to predict the bottomhole flowing pressure in vertical wells.
2. The new model provided exceptionally accurate predictions over the best available empirical correlations and mechanistic models.
3. The developed model achieved best correlation coefficient (0.9735), the lowest maximum absolute relative error (7.1401%), the lowest root mean squared error (2.8013), the lowest standard error deviation (66.2448), and the lowest average absolute percent error (2.1654%).
4. Trend analysis of the model showed that the model correctly predicted the expected effects of the independent variables on bottomhole flowing pressure. This indicated that the model simulates the actual physical process.
5. The present study clearly demonstrates the power of artificial neural network model in solving complicated engineering problems. The developed model could perform even better if more data were used for training.
6. The new developed model can be used only within the range of used data. Caution should be taken beyond the range of used input variables.

Acknowledgment

The authors would like to thank King Fahd University of Petroleum and Minerals for supporting this work and Saudi Aramco for providing the data used in this study.

APPENDIX

1. Average Percent Relative Error (APE):

It is the measure of relative deviation from the experimental data, defined by:

$$E_r = \frac{1}{n}\sum_{i=1}^{N} E_i$$

Where; E_i is the relative deviation of an estimated value from an experimental value

$$E_i = \left[\frac{(BHP)_{meas} - (BHP)_{est}}{(BHP)_{meas}}\right] \times 100, \quad \mathrm{i} = 1,2,3,...,\mathrm{n}$$

Where

$$\overline{\Delta BHP} = \frac{1}{n}\sum_{I=1}^{n}[(\Delta BHP)_{act}]_I$$ where;

$(BHP)_{meas}$ is the actual value of bottomhole pressure

$(BHP)_{est}$ is the estimated value of bottomhole pressure

2. Average Absolute Percent Relative Error (AAPE):
It measures the relative absolute deviation from the experimental values, defined by:

$$E_a = \frac{1}{n}\sum_{i=1}^{n}|E_i|$$

(This will be considered as the main criterion in statistical error analysis throughout this study).

3. Minimum Absolute Percent Relative Error:

$$E_{\min} = \min_{i+1}^{n}|E_i|$$

4. Maximum Absolute Percent Relative Error:

$$E_{\max} = \max_{i+1}^{n}|E_i|$$

5. Root Mean Square Error:
Measures the data dispersion around zero deviation, defined by:

$$RMSE = \left[\frac{1}{n}\sum_{i=1}^{n}E_i^{\ 2}\right]^{0.5}$$

6. Standard Deviation:
It is a measure of dispersion and is expressed as:

$$STD = \sqrt{\left[\left(\frac{1}{(m-n-1)}\right)\right]\sum_{i=1}^{m}\left[\left\{\frac{(BHP_{act} - BHP_{est})}{BHP_{act}}\right\}100\right]^2}$$

Where; (m-n-1) represents the degree of freedom in multiple-regression. A lower value of standard deviation indicates a smaller degree of scatter.

7. The Correlation Coefficient:
It represents the degree of success in reducing the standard deviation by regression analysis, defined by:

$$R = \sqrt{1 - \frac{\sum_{I=1}^{n}[(BHP)_{act} - (BHP)_{est}]}{\sum_{I=1}^{n}(BHP)_{act} - \overline{\Delta BHP}}}$$

'R' values range between 0 and 1. The closer value to 1 represents perfect correlation whereas 0 indicates no correlation at all among the independent variables.

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Table 1: Statistical Analysis of the Used Data.

Property	Training Data (106 sets)			Validation Data (41 sets)			Testing Data (41 sets)		
	Min	Max	Avg.	Min	Max	Avg.	Min	Max	Avg.
Bottomhole pressure, psi	1227	3217	2222	1911	3124	2517.5	1906	2984	2445
Oil rate, bbl/d	280	19618	9949	469	17243	8856	840	16437	8638.5
Gas rate, mscf/d	33.6	13562.2	6797.9	81.6	12586	6333.8	134.4	8278.1	4206.2
Water rate, bbl/d	0	11000	5500	0	9300	4650	0	10500	5250
Tubing diameter, inches	1.995	4	2.9975	2.441	4	3.2205	3.813	4	3.9065
Depth, ft	4550	7100	5825	4964	7043	6003.5	4550	6933	5741.5
API, (oil gravity)	30	37	33.5	30	37	33.5	30	37	33.5
Surface temperature, ^oF	76	160	118	90	160	125	90	159	124.5
Bottomhole temp., ^oF	157	215	186	162	215	188.5	162	214	188
Wellhead pressure, psi	80	780	430	95	960	527.5	180	750	465

Table 2: Statistical Analysis Results of Empirical Correlations and Mechanistic Models

MODEL	E_a	E_r	E_{Max}	E_{Min}	RMSE	R	STD
Kabir and Hasan[15]	9.230	-7.190	35.140	0.486	11.944	0.7502	215.644
Ansari *et al.*[18]	6.754	-1.451	16.612	0.025	8.089	0.8178	196.930
Chokshi *et al.*[19]	5.759	-2.852	17.843	0.355	7.009	0.8836	155.684
Gomez *et al.*[20]	5.204	1.212	26.617	0.019	7.643	0.8324	184.069
Hagedorn and Brown[2]	5.029	1.461	26.569	0.141	7.373	0.8508	177.840
Duns and Ros[3]	5.758	-2.834	20.437	0.009	7.564	0.8495	173.083
Orkiszewski[4]	5.376	4.617	20.592	0.042	7.251	0.9015	138.053
Beggs and Brill[5]	5.690	-1.892	19.533	0.326	7.144	0.8647	167.755
Mukherjee and Brill[7]	4.903	-1.164	16.209	0.201	6.217	0.8792	147.572
This Study "ANN"	2.165	-0.419	7.1401	0.066	2.801	0.9735	66.245

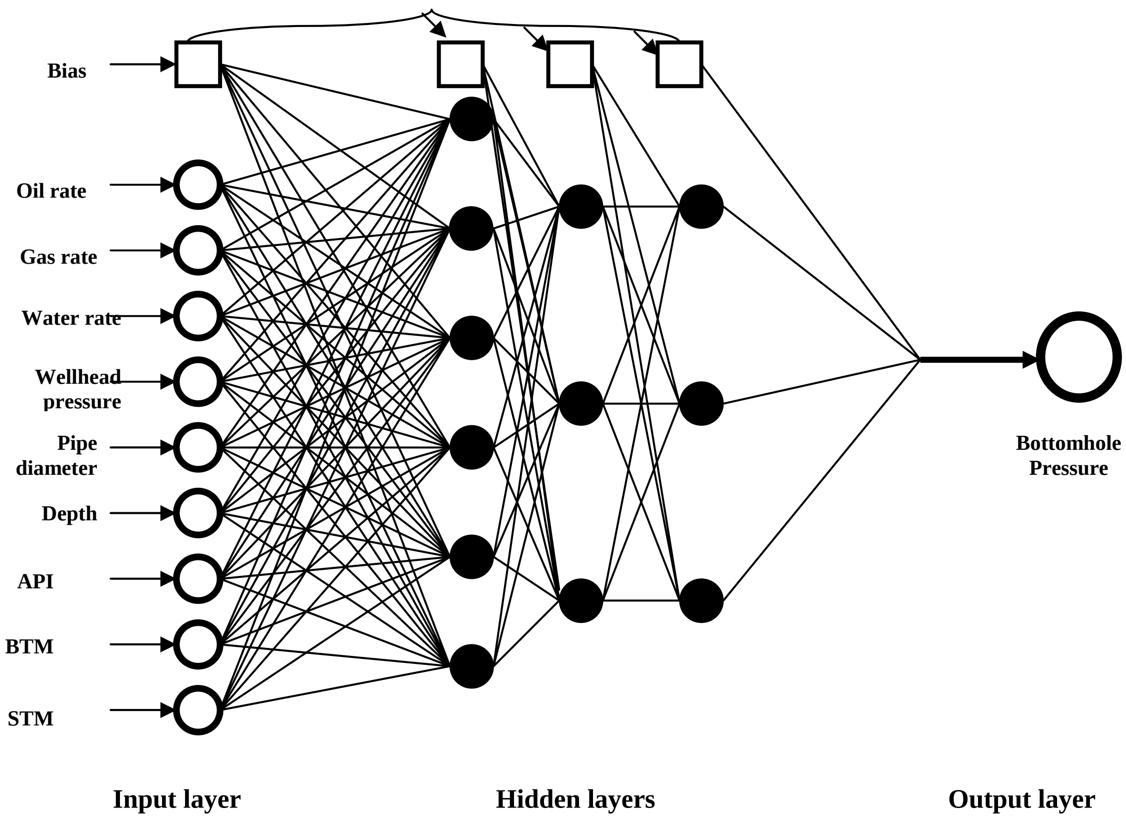

Figure 1: Schematic of the Developed Model.

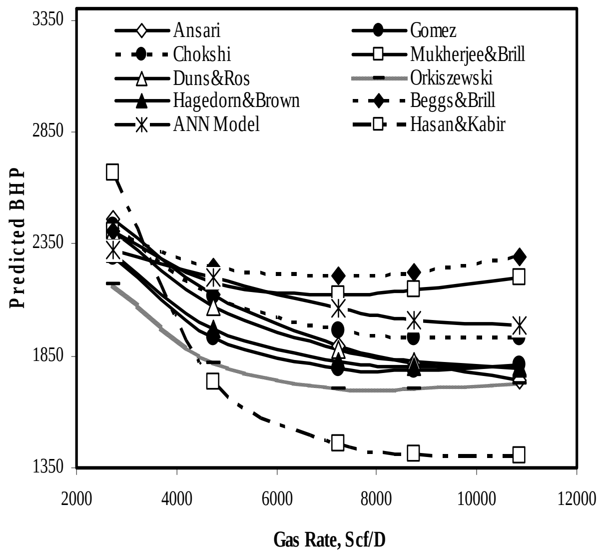

Fig. 2 Effect of Gas Rate on BHP, D= 3.958 in.

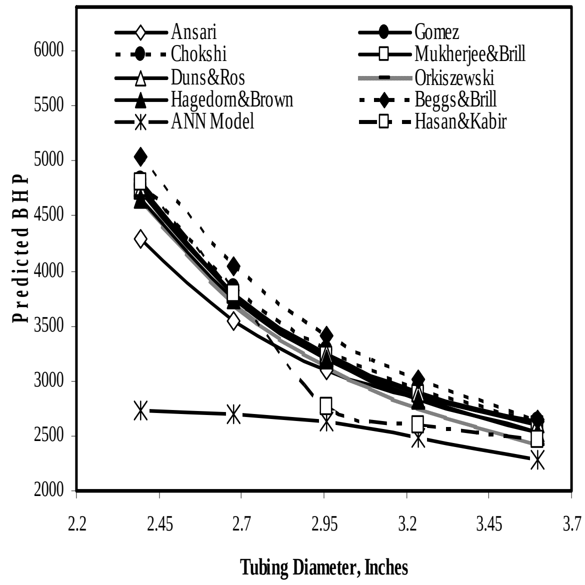

Fig. 3: Effect of Tubing Diameter on BHP.

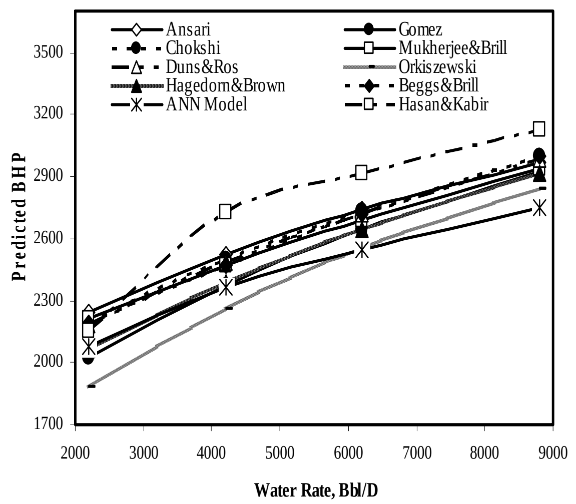

Fig. 4: Effect of Water Rate on BHP, D = 3.958 in.

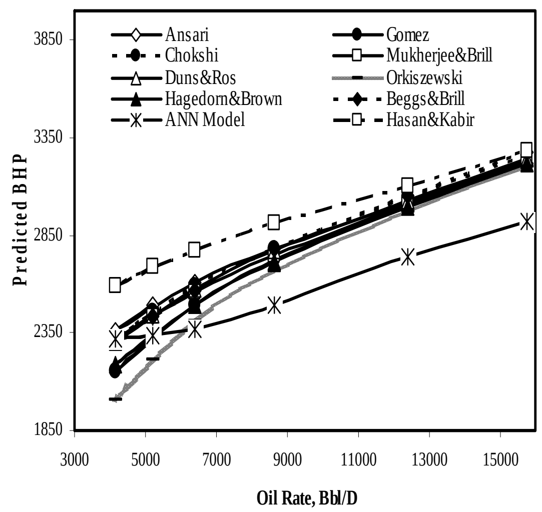

Fig. 5: Effect of Oil Rate on BHP, D=3.958 in.

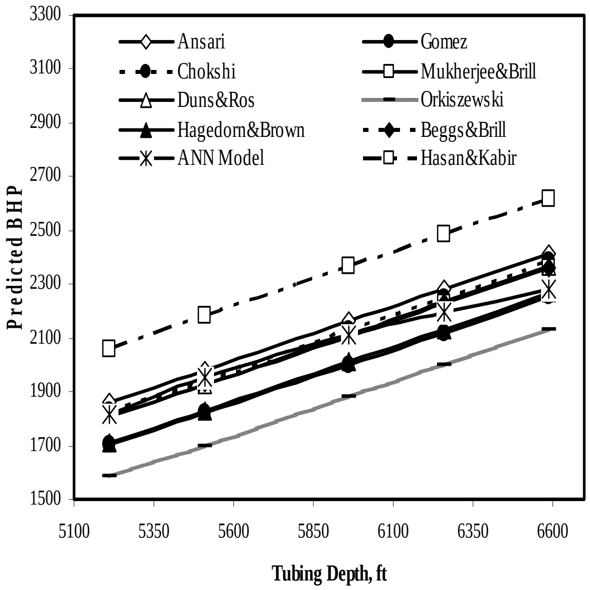

Fig. 6. Effect of Pipe Length on BHP, D=3.958 in.

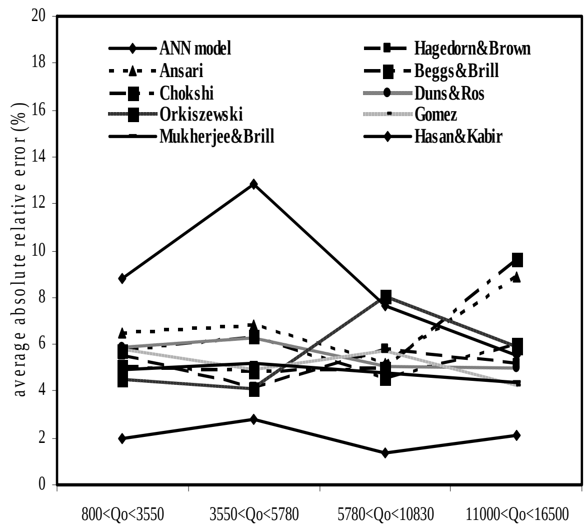

Fig. 7: Statistical Accuracy of BHP Grouped by Oil Rate.

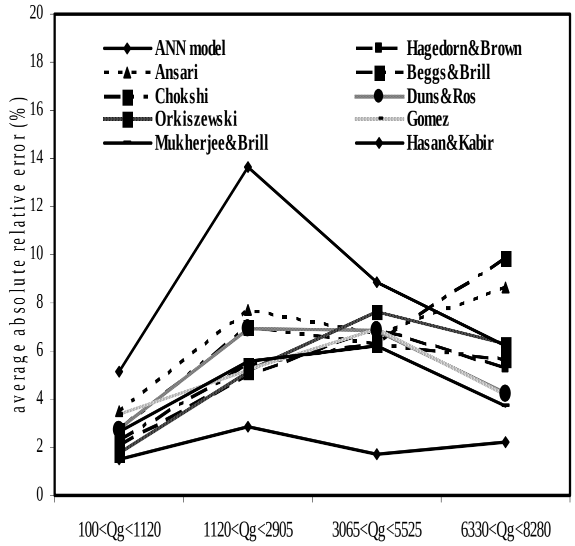

Fig. 8: Statistical Accuracy of BHP Grouped by Gas Rate.

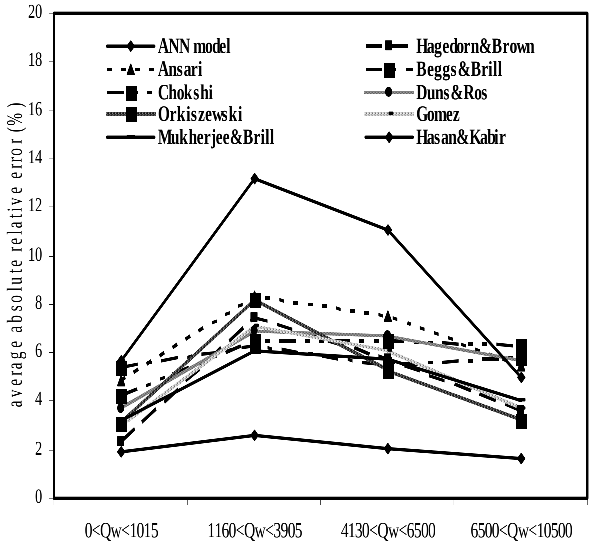

Fig. 9: Statistical Accuracy of BHP Grouped by Water Rate.

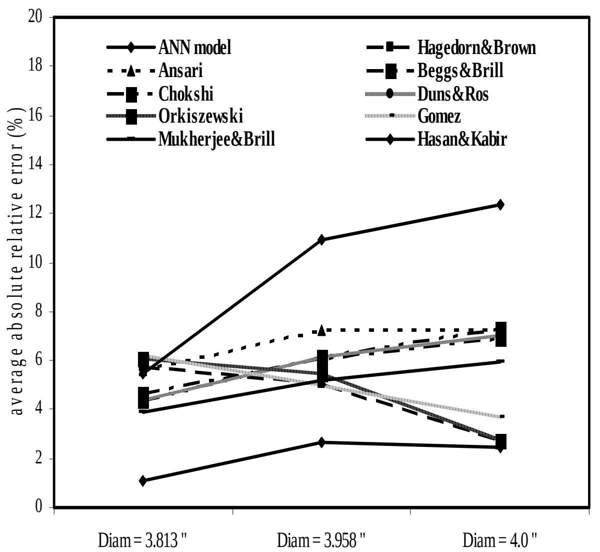

Fig. 10: Statistical Accuracy of BHP Grouped by Tubing Size.

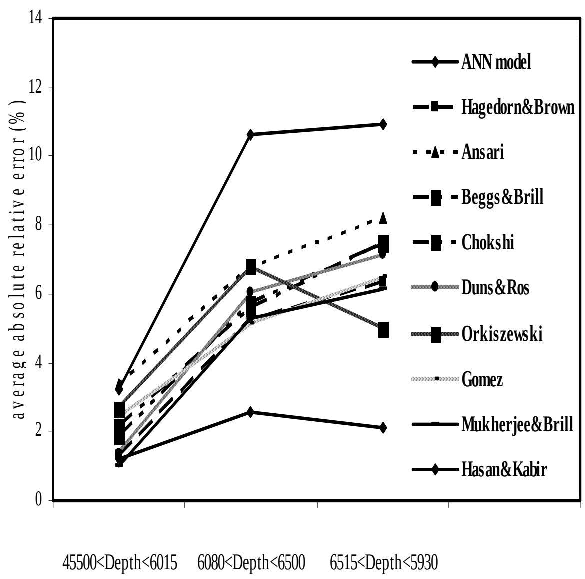

Fig. 11: Statistical Accuracy of BHP Grouped by Tubing Depth.

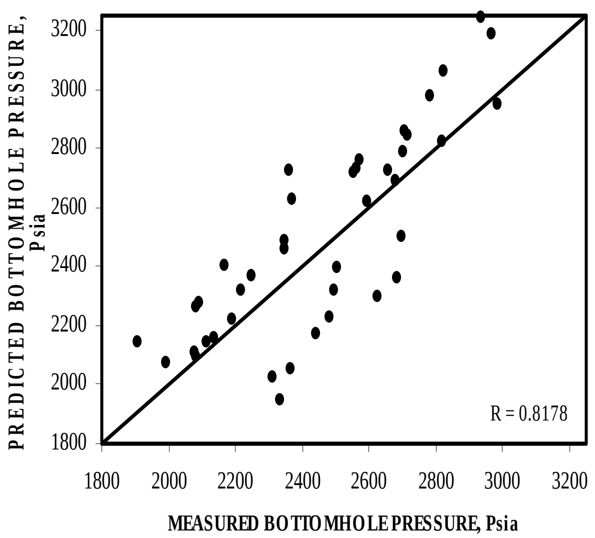

Fig. 12: Cross plot of BHP for Ansari *et al.* Model.

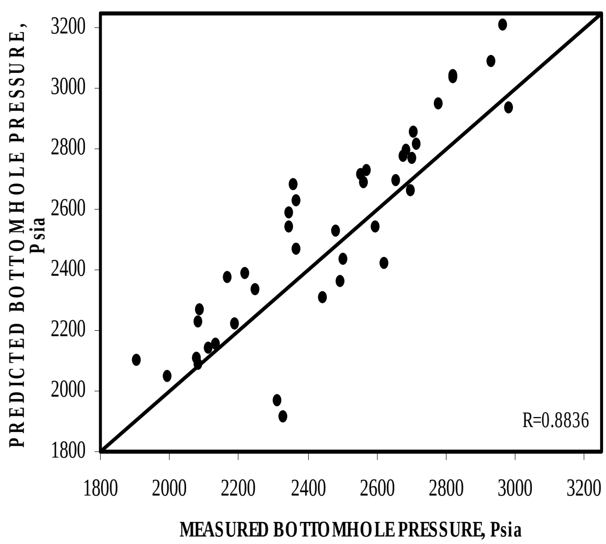

Fig. 13: Cross plot of BHP for Chokshi *et al.* Model.

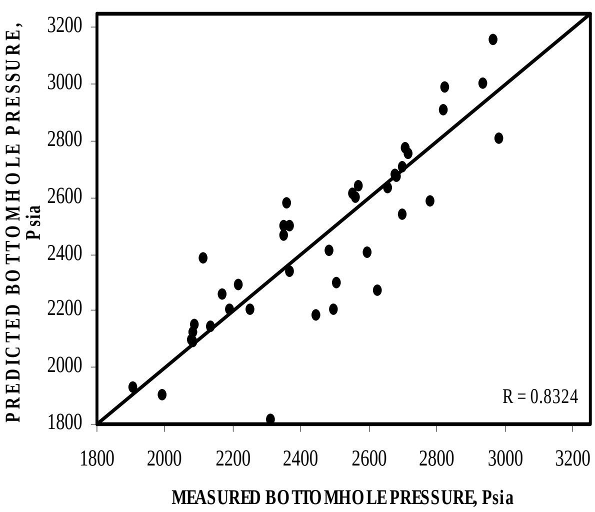

Fig. 14: Cross plot of BHP for Gomez *et al.* Model.

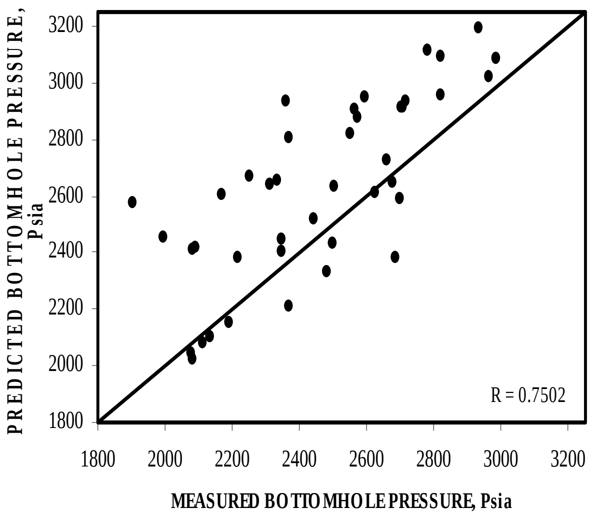

Fig. 15: Cross plot of BHP for Hasan and Kabir Model.

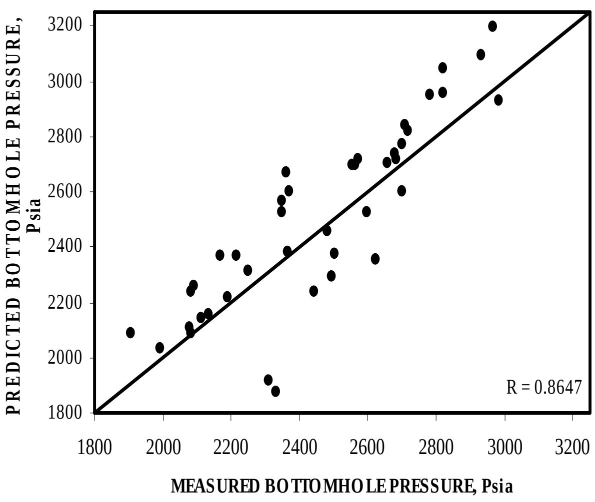

Fig. 16: Cross plot of BHP for Duns and Ros Correlation.

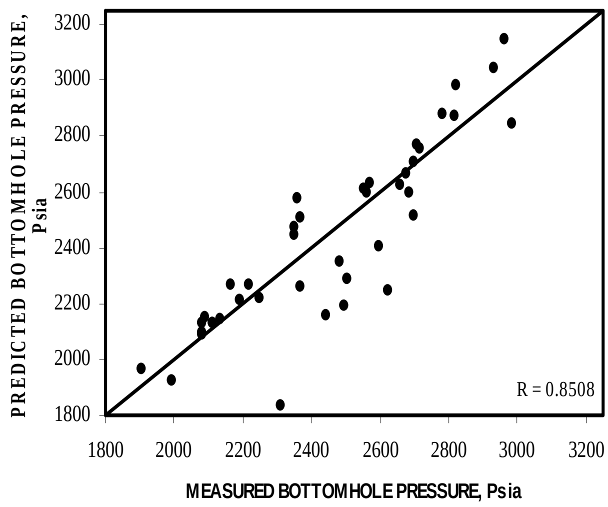

Fig. 17: Cross plot of BHP for Chokshi *et al.* Model.

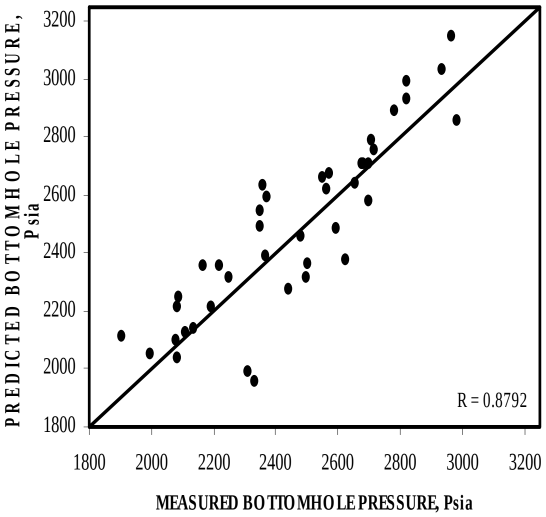

Fig. 18: Cross plot of BHP for Mukherjee and Brill Correlation.

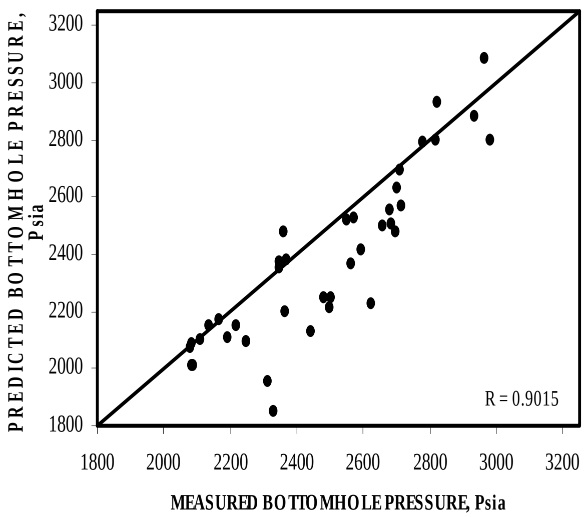

Fig. 19: Cross plot of BHP for Orkiszewski Correlation.

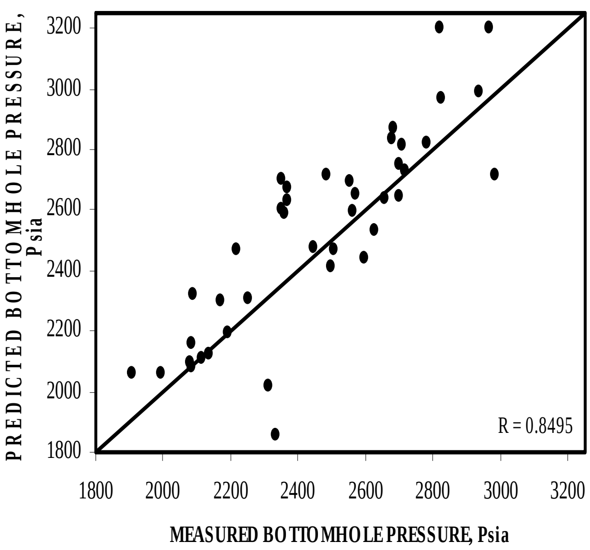

Fig. 20: Cross plot of BHP for Beggs and Brill Correlation.

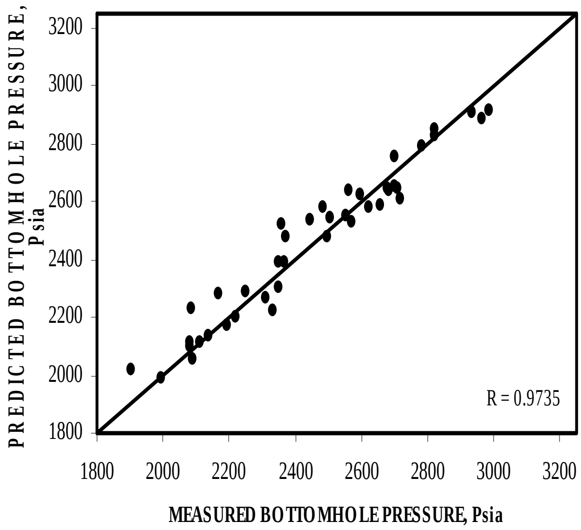

Fig. 21: Cross plot of BHP for Present ANN Model.