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Accurate Prediction of Pressure Drop in Two-Phase Vertical Flow Systems using Artificial Intelligence

Ahmed Al-Shammari, Saudi Aramco

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Abstract

One of the significant parameters affecting flow rate in oil production wells is the pressure drop between the well bottom-hole and tubing head. The pressure drop calculation in two-phase flow systems is very complicated due to the variations in gas and liquid flow rates across the two-phase flow stream. As the pressure of crude decreases while climbing a well tubular, more gas comes out of solution. This gradual increase in gas volumes leads to the reduction of liquid slip velocity and creating new flow patterns that are not only different in shape, but also complicated in pressure drop calculations. To overcome this difficulty in calculating pressure drop in two-phase flow systems, scientists came up with two main approaches: flow correlations and mechanistic models. These two approaches are applicable within certain conditions and their accuracy in pressure drop prediction degrades outside their design boundary ranges.

The raising popularity of Artificial Intelligence (AI) techniques during the past two decades proved that AI can be an alternative solution to many of the complicated problems where physics and classic statistics fail to provide satisfactory solutions. These techniques applied in different upstream fields have provided fast, robust and reliable numerical models in a variety of areas, e.g., geological modeling, reservoir engineering, petrophysics and well testing. This paper describes the utilization of Fuzzy Logic, which is one of the famous AI techniques, in predicting flowing bottom-hole pressure in oil producer wells. Real well testing data from the Middle East were used in constructing the Fuzzy Logic model. After training the model using 596 well testing data samples, it was successfully able to predict the flowing bottom-hole pressure at 199 well testing samples with an average absolute error of 4.9%. A comparison analysis was conducted to evaluate multiple flow correlation in predicting flowing bottom-hole pressure and compare their results with the developed Adaptive Neuro-Fuzzy Inference System (ANFIS) model.

Introduction

The determination of flowing bottom-hole pressure (BHP) in oil wells is very important for petroleum engineers. It helps in designing production tubing, determination of artificial lift requirements and in many of other production engineering aspects such as avoiding producing a well below its bubble point in the sand-face to maintain completion stability around the wellbore. With the increased utilization and deployment of permanent down-hole gauges, measuring flowing bottom-hole pressure is becoming easier and faster. These gauges require continuous maintenance and calibration to avoid erroneous readings. In addition, the design of new wells requires predicting the BHP under different conditions of wellhead pressure, tubing sizes, liquid rates, water cut and gas oil ratios.

Pressure Drop Calculations

Fluid flow rate in a pipe is directly proportional to the pressure difference between the pipe inlet and outlet. Considering a pipe with fixed inside diameter and fluid flow under steady-state conditions, there are two main types of pressure losses: gravitational and frictional.

Gravitational Pressure Drop

Gravitational pressure drop occurs only if there is a change in elevation between a pipe inlet and outlet. Gravitational pressure difference is directly proportional to the vertical elevation change and the fluid specific gravity. The amount of pressure drop in field units due to gravity can be calculated using equation[1] 1:

$$\Delta P_{Gravity}(\text{psi}) = 0.433\ SG_m\ L\ \sin\theta^{o} \quad (1)$$

Where: SG_m is the mixture specific gravity, L is tubing depth (ft) and θ is the inclination angle

In oil producer wells with low to average GOR values, the gravitational pressure drop is the major contributor to the total pressure losses between a well sand-face and tubing head. In oil wells with GOR values around 500 scf/bbl, 80 – 85% of the total pressure drop is due to gravitational losses and the rest would be mostly frictional. As the GOR increases, frictional pressure losses start to dominate the total pressure drop due to the increase in fluid mixture velocity and the reduction of liquid holdup.

Frictional Pressure Drop

Frictional pressure loss occurs due to shear forces acting against fluid flow direction. The frictional losses happen near the pipe inner surface due to the molecular interconnectivity forces that resist the deformation. These forces are directly proportional to the kinetic energy of the fluid element and to the friction factor, which can be determined experimentally. Several scientists tried to correlate the friction factor with different flow parameters.

In 1944, Lewis Moody published “Friction Factor for Pipe Flow” (1). The work of Moody has become the basis for many of the calculations on friction loss in pipes. Colebrook and White came up with an implicit relationship (equation 2) for calculating friction factor (2).

$$\frac{1}{\sqrt{f}} = 1.74 - 2\log\left(\frac{2\varepsilon}{d} + \frac{18.7}{N_{\mathrm{Re}}\sqrt{f}}\right) \quad (2)$$

This equation was then solved by Swamee and Jain (3) to give an explicit approximated solution as in equation 3:

$$\frac{1}{\sqrt{f}} = 1.14 - 2\log\left(\frac{\varepsilon}{d} + \frac{21.25}{N_{\mathrm{Re}}^{0.9}}\right) \quad (3)$$

[1] “Sami Al-Nuaim, class lecture for “Advanced Well Performance,” KFUPM, March 2009”

Where $\mathcal{E}$ the absolute pipe roughness (ft), d is the pipe diameter (ft) and N_{Re} is the Reynolds number

The pressure drop due to friction in single phase can be calculated as[1]:

$$\Delta P_f\,(psi) = 1.8375 * 10^{-7}\,\rho\,f\,L\,\frac{q^2}{d^5} \quad \ldots\ldots (4)$$

Where: ρ is the single phase fluid density (lb/ft^3), f is the friction factor (dimensionless), L is tubing depth (ft), q is flow rate (bpd) and d is tubing diameter (in)

Pressure Drop Calculations in Oil Producer Wells

As described above, the total pressure drop in oil wells is composed of gravitational and frictional pressure drops. To calculate the total pressure drop along a production tubing section, one needs to determine the amounts of gas and liquid and trace their changes vertically. The vertical flow inside a tubing section is accompanied with pressure reduction and as the pressure reaches the bubble point, gas bubbles begin to be released. These bubbles slip vertically through the liquid column and start to accumulate as more bubbles are formed with the pressure decrease. The accumulation of gas bubbles results in forming larger bubbles that grow more as the flow climbs the tubing section, creating what is called slug flow. As the pressure continues to decrease and yet more gas is still to be released out of solution, the gas phase might transform into continuous phase at the center of the pipe and the oil phase will flow as a thin fluid ring on the inside wall of the tubing. These changes in fluid-gas phase patterns are known as flow regimes, which are predicted based on empirical formulas that were developed numerically in the lab.

It is obvious to say that both gravitational and frictional pressure losses will be different depending on the flow regime, which results in complicating the approaches for calculating total pressure drop in oil wells.

Typically; the two-phase flow correlation approaches calculate pressure drop by dividing the wellbore into segments and then determining the pressure drop iteratively in all segments, which eventually leads to calculating the pressure at the flow stream outlet. This is illustrated in figure 1.

For determining BHP starting from WHP, the process can be described as follows:

1- Divide the wellbore into segments.
2- Assume P_2 at the first segment outlet.
3- Calculate average pressure of the segment based on P_1 and assumed P_2 .
4- Calculate GOR and FVF for Oil & Gas at P_{ave} to come up with liquid holdup.
5- Determine flow pattern based on holdup and inclination angle.
6- Calculate two phase density at P_{ave} .
7- Calculate $\Delta P_{gravity}$.
8- Find Reynolds number and friction factor.
9- Calculate $\Delta P_{friction}$.
10- The pressure at outlet P_2 is calculated based on $P_2 = P_1 - \Delta P_{total}$.
11- Compare calculated P_2 with the initially assumed P_2. If they match within a tolerance, then consider P_2 to be the inlet pressure for the subsequent segment. Otherwise, consider P_2 (assumed) = P_2 (calculated) and go to step #2.

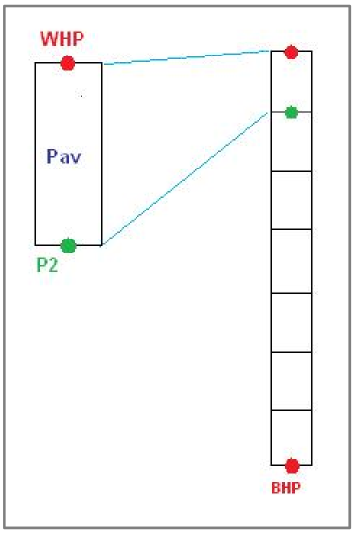

Figure 1: Pipe segmentation to calculate pressure drop iteratively.

[1] "Sami Al-Nuaim, class lecture for "Advanced Well Performance," KFUPM, March 2009"

The above steps indicate the complexity in calculating pressure drop for oil producer wells using two-phase flow correlations. Most of the computation steps involve the utilization of empirical correlations that were developed based on statistical and curve fitting techniques.

Majority of the developed two-phase flow correlations and mechanistic models were constructed with limited conditions and their error in predicting pressure drop tends to increase as the conditions start deviating from the design boundaries. There is no available single correlation or mechanistic model that can be applicable for all ranges of production such as GOR, liquid rate, tubing size or watercut. (4)

What is Fuzzy Logic?

The term "Fuzzy" refers usually to uncertainty, ambiguity or something not well defined. Most of the natural physical properties can be described by non-crisp terms such as hot, cold, bright, hard, strong, etc. The human thinking, reasoning and decision making processes are also not crisp. We use vague, imprecise words to explain our thoughts or communicate with one another (5). Fuzzy systems are usually used to represent uncertainty that is caused by inaccuracy or ambiguity of the data or lack of the input parameters that have an important influence on results.

In fuzzy systems, an item, a behavior or a property can be described by classifying it under one of different non-crisp sets in addition to a degree of membership to each set. (6)

Let us take for example an AC temperature setting and define the human feeling at each temperature as different fuzzy sets. We could consider 16^{o}C to be cold, 22^{o}C as pleasant and 26^{o}C as hot. The three sets here are: cold, pleasant and hot and each temperature setting can belong to one of these sets at a degree of membership. Take for example, the temperature 25^{o}C, is it pleasant or hot? Actually, it can belong to the two sets at the same time but with a different degree of membership. We can say that it is not very pleasant or it is a little hot. This can be described graphically in Figure 2, where the membership value of 25^{o}C is 0.75 with Pleasant property and 0.25 with Hot property.

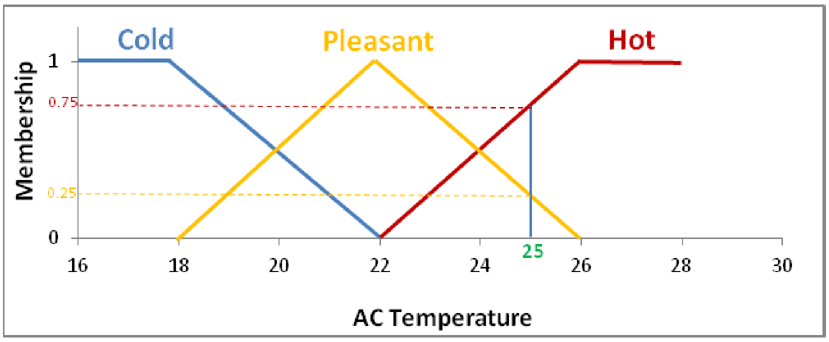

Figure 2: Describing temperature using fuzzy sets

One way of representing fuzzy set and membership information is $\mu A(x) = m$, where the membership μ of an item x in a fuzzy set A is m. The AC temperature example can be expressed by the following expression:

$$\mu_{Hot}(25) = 0.75 \text{ or } \mu_{Pleasant}(25) = 0.25$$

In fuzzy logic, unlike representing a normal set like A = {x | x is even number}, we describe fuzzy sets by coupling elements with membership functions such as $A = \{x, \mu A(x) \mid x \in X\}$. The membership functions can be simple straight lines or advanced functions such as trapezoidal, sigmoid or Gaussian. (7)

The Fuzzy Inference System (FIS) is the process of establishing formulated mapping from an input to an output using fuzzy logic. FIS involves combing formulating membership functions, logical operations and a group of "If-Then" rules to create a matrix of rules between input sets and an output.

The Use of Fuzzy Logic in the Petroleum Industry

Fuzzy Logic has been used in several petroleum engineering-related applications. These include petrophysics and permeability determination, stimulation candidate selection, production optimization and completion and multilateral design.

In 2000, S.J Cuddy (8) described the application of Fuzzy Logic in determining litho-facies and permeability in uncored wells. In his study, he used data for 10 cored wells to derive litho-facies and permeability in 30 uncored wells.

Ali Garrouch, et. al. of Kuwait University (9) developed in 2003 a new Fuzzy Logic for designing optimal multilateral well configuration and completion. They formulated reservoir candidate screening criteria for applying multilateral technology, and implemented these criteria in a new expert system that features the use of fuzzy logic for handling ambiguity in completion scenarios.

Similar to Cuddy methodology in finding permeability, in 2005, M. Amabeoku et. al. published a paper describing the use of Fuzzy Logic to model and predict permeability in cored wells by calibrating core permeability against conventional open-hole logs (10). The permeability models developed were then used to generate permeability trace in each well across a field.

Fuzzy logic was also used to predict reservoir fluid viscosity. In 2007, Yasin Hajizadeh published this work, which included using both ANN and fuzzy logic in predicting oil viscosity (11). He used both techniques to recognize the pattern between the given data sets where this pattern may not be understood clearly or no precise mathematical relationship exists.

One of the recent studies that utilized Fuzzy Logic modeling was to determine inflow performance relationship in horizontal oil wells. This study was conducted by Ebrahimi, M in 2010 (12). The author tried two neuro-fuzzy models, including Local Linear Neuro-Fuzzy Model and Adaptive Neuro Fuzzy Inference System and compared the performance with empirical correlations to predict inflow performance of horizontal oil wells experiencing two phase flow.

Adaptive Neuro-Fuzzy Inference System (ANFIS)

ANFIS method provides a technique for fuzzy modeling process to "learn" from data sets. This method is applied to construct an FIS and tuning or adjusting the membership functions using back propagation algorithms along with least-square type functions to learn from datasets. A structure similar to neural networks is created to map inputs using input membership functions and associated parameters, and then through output membership functions and associated parameters to the outputs.

Developing the ANFIS Model

Data Acquisition

Data preparation is one of the key steps in developing any AI technique. It is very important to review the data and remove outliers before using it in constructing AI models. For the current study a total of 1207 well productivity testing data sets were initially collected from several fields in the Middle East. The data sets included several key input parameters that were later used in constructing the ANFIS model. The input parameters selected were: flowing wellhead pressure, liquid rate, watercut %, gas oil ratio, oil API, reservoir temperature, tubing inside diameter and the gauge depth. The output value was the measured flowing pressure at gauge depth.

Data Preprocessing and Filtration

Well testing data is subject to uncertainty and inaccurate measurements, so it is important to filter the data and exclude all the datasets that include one or more of these inaccurate readings that might disturb the smoothness of the model learning process. The filtration process was done by applying the following steps:

1- A small computer program was written to feed well testing conditions (data sets) into Prosper software to calculate flowing bottom-hole pressure using multiple flow correlations. The correlations used were: Beggs and Brill, Duns and Ros, Hagedorn and Brown, Fancher and Brown, Mukherjee and Brill, Orkiszewski and Petroleum Experts II.

2- The relative absolute error between the predicted and measured flowing bottom-hole pressure was calculated for each of the correlations.

3- The arithmetic average error for all the correlations was computed at each dataset.

4- Datasets at which the average error is more than 15% were excluded from the study.

After filtering the data, we ended up having a total of 796 datasets. A summary of the data parameter ranges is available in table 1.

		Min	*Max*
Input	WHP (psig)	92	1550
	Q_{Liquid} (bpd)	639	21300
	WC (%)	0	97.5
	GOR (scf/stb)	11	6300
	Depth (ft)	4243	8620
	ID (in)	1.995	6.276
	API	25.4	47.5
	T res (^{o}f)	160	233
Output	BHP (psig)	1198	3698

Table 1: Data ranges of input and output parameters in this study

ANFIS Model Development

In this study, Matlab software was used for designing and optimizing the fuzzy logic system. Matlab has a large library of functions and techniques that are used for constructing most of the AI models. There are two main types of FISs available: Mamdani and Sugeno. In this study, we implemented Sugeno type FIS because it is more compact and has a more efficient representation of the rules. (7)

The technique used in creating the FIS for this study was to implement subtractive clustering method that groups the data into multiple clusters and each cluster is defined by a radius of influence whose values range between 0 and 1. Small value of cluster radius results in a larger number of rules and usually tends to over fit the trainin data. Each value of the input variables is then linked to a cluster by a membership function that is fine-tuned iteratively until the model predicts an output with minimal deviation from target value.

Several FIS techniques were tested in Matlab to come up with the most optimized technique. It was found that the Matlab function: "*genfis2"* provides superior modeling results during the training stage and hence used for further optimization. This function generates Sugeno-type FIS structure using subtractive clustering of the data and extracts rules and membership functions to model the data behavior. (7)

Among the 795 well testing data samples, 596 data samples (75%) were used for training and 199 (25%) for testing. Table 2 summarized the ranges for the training and testing data to insure most of the data ranges are similar in both.

	Training		*Testing*	
	Min	***Max***	***Min***	***Max***
WHP (psig)	92	1550	170	1410
Q_{Liquid} (bpd)	639	21230	1000	21300
WC (%)	0	97.5	0	93.7
GOR (scf/stb)	18	6140	11	6300
Depth (ft)	4243	8620	4650	8478
API	25.4	47.5	26.2	47.5
ID (in)	1.995	6.276	2.441	6.276
T res (^{o}f)	160	233	160	233
BHP (psig)	1198	3604	1705	3698

Table 2: Data ranges of input and output parameters for training and testing

Model Optimization

After testing several cluster radii, it was found that a cluster radius of 0.6 was the most optimized value with an average absolute error of 4.33 % and 4.92% on the training and testing data respectively. Figure 3 indicates the effect of cluster radius on the error standard deviation, the average absolute error and correlation factor between predicted and measured BHP.

The figure indicates that small cluster radius has a good impact on predicting the BHP for the training data samples. This results in a large number of rules that almost memorized the data blindly, which has a bad influence on the prediction of the BHP using testing samples.

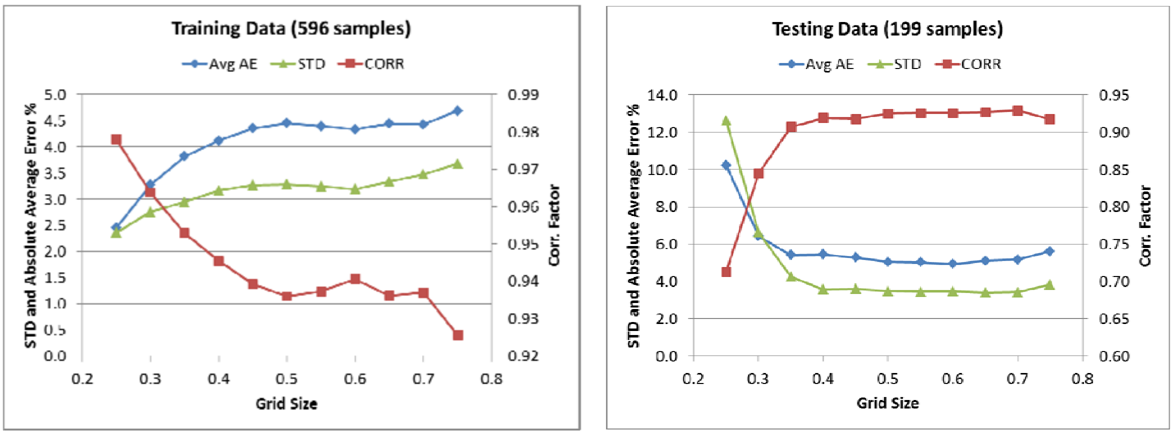

Figure 3: Model optimization based on cluster radius

Results and Analysis

The ANFIS model was able to model the flowing bottom-hole pressure with higher accuracy than all the flow correlations included in the study. The average absolute error, the maximum error and correlation factor between the measured and predicted BHP applied on the testing data were: 4.3%, 14.9% and 0.94 respectively and the standard deviation of the errors was 3.3. Tables 3 summarizes the performance of the ANFIS model and all the flow correlations included in the study, based on the testing of data samples. The first and second columns indicate the average (AAE) and maximum (MAE) absolute error percentages between the measured and the predicted BHPs using each of the models. The third column has the correlation coefficients (CC) between the predicted and measured BHPs. And the last column shows the standard deviation of the errors.

Model	AAE (%)	MAE (%)	CC	SD
Duns and Ros	8.94	19.31	0.89	5.37
Fancher and Brown	7.56	23.62	0.90	5.14
Hagedorn and Brown	7.21	21.07	0.90	4.80
Orkiszewski	7.16	37.49	0.89	5.18
Beggs and Brill	6.95	19.21	0.92	4.56
Petroleum Experts II	6.30	17.56	0.91	4.47
Mukherjee and Brill	6.06	14.95	0.91	4.14
ANFIS	4.93	14.91	0.93	3.48

Table 3: Results summary

Plots of the measured and predicted pressures for training and testing data samples are shown in figures 4 and 5. The "slope 1" plots of the predicted vs. measured pressures for both training and testing samples are shown in figures 6. These plots show even distribution of the data around the slope 1 line, which indicates that there is no trend in the prediction behavior.

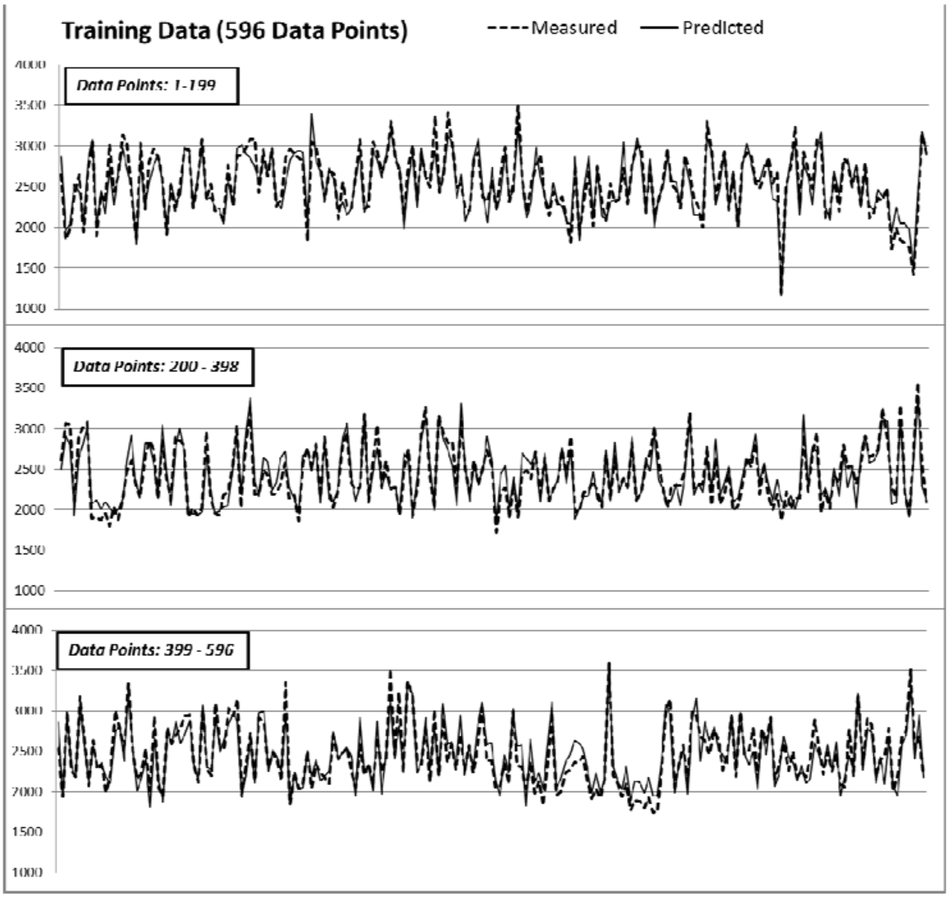

Figure 4: Results of the training data samples

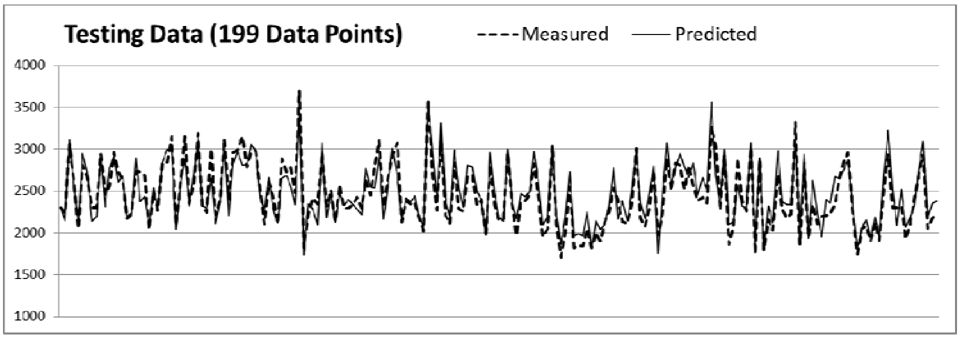

Figure 5: Results of the Testing Data Samples

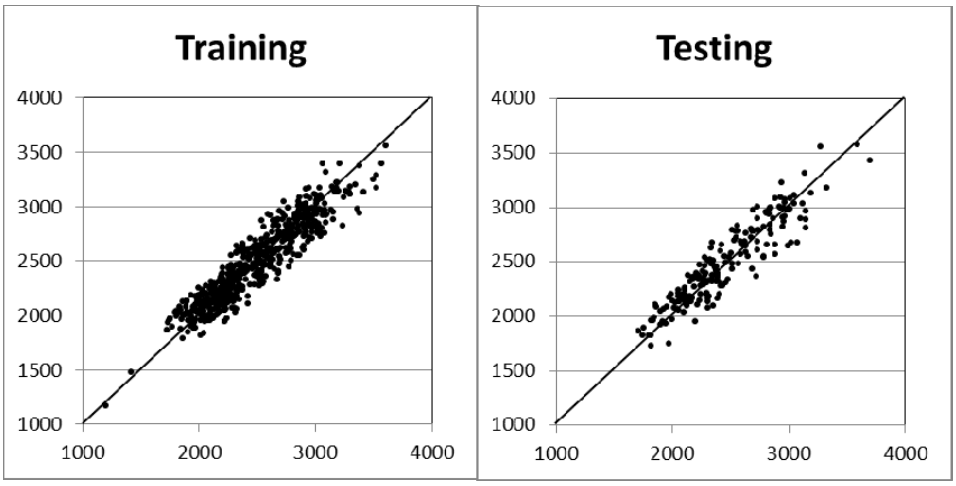

Figure 6: Predicted pressure vs. measured pressure for training and testing data samples

Conclusion

Predicting flowing bottom-hole pressure is one of the challenges in the petroleum industry due to the complication that arises in the two-phase flow systems. In this study, an Adaptive Neuro-Fuzzy Inference System was developed using subtractive clustering with a cluster radius of 0.6, to predict flowing bottom-hole pressure with higher accuracy than all of the correlation models included in the study. The data ranges used in the study cover most of the applicable conditions in the petroleum industry. The model prediction behavior can be negatively affected when trying to predict BHP outside the data ranges.

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