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Virtual Measurement in Pipes, Part 1: Flowing Bottom Hole Pressure Under Multi-Phase Flow and Inclined Wellbore Conditions

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Abstract

Pressure drop prediction in pipes is an old petroleum engineering problem. There is a long history of attempts to develop empirical correlations to predict the pressure drop in pipes. Some of these attempts have produced correlations that provide good prediction in some cases. However, their general applicability is questionable. Correlations that address only a specific class of problems exist. These types of correlation usually perform better than those which attempt to meet the need of a variety of problems. Usually, the higher the number of variables in the model the lesser the reliability and general applicability of the correlations. This is the result of using methodologies such as conventional regression analysis. In such methodologies, the chances of correctly and completely capturing the relationship between variables decreases as the number of variables increases. Many parameters could be involved in these types of problems, such as gas-oil ratios in two phase systems, water flow in three phase systems, and inclination angles of the pipe, to name a few. In this paper, the authors introduce a new methodology for developing prediction models for pipes. This method which has been named Virtual Measurement in Pipes (VMP), incorporates artificial neural networks (ANN) to address the development of tools to predict pressure drops in pipes and optimum design of pipelines under a variety of circumstances.

The fundamental problem with conventional approaches resides in the inherent sequential and pointwise (as opposed to parallel and distributed) information processing methods used in development of such correlations. Because of this shortcoming, conventional methodologies are unable to address, define, or unravel the highly complex relationships between many variables involved in the process. In this paper, artificial neural networks are used to develop a Virtual Measurement Tool to survey flowing bottom hole pressure (BHP) in multi-phase systems using information such as oil, gas and water flow rates, temperature, oil and gas gravity, pipe length, surface pressure, and inclination angles of the pipe. The developed Virtual Measurement Tool has been applied to the published field data for flowing BHP predictions. VMP's predictions are compared to existing methods and the enhancement is clearly demonstrated.

The developed VMP is applied to wellbore hydraulic problems. It addresses three-phase (oil, water, and gas) flow in wellbores. This tool applies to a variety of wells, including vertical wells and those with various degrees of inclination.

Introduction

Concurrent flow of oil and gas occurs as the fluids pass through the sequential parts of the production system, which include tubing, pipelines, separators, treaters, and heat exchangers. Optimum pipe size is an important factor that determines the feasibility of the operations. Among different components, the production tubing has the utmost importance in maximizing the reservoir energy in naturally flowing and artificial lift wells. The problem of interest here is the ability to predict the relationship between fluid properties and rates, and the pressure drops under varying physical conditions like pipeline size and tubing diameter.

The pressure drop prediction in a multiphase flow system is a very complicated problem. In general a total energy balance between two ends of the tubing under investigation is used to determine the pressure drop and flow rates.[1-4] The three components of the pressure drop equation deal with elevation, friction, and acceleration of fluid in the tubing. Resulting steady state equations are coupled with experimentally determined multiphase fluid properties yielding a semi-empirical approach. Due to the many flow patterns with different geometry and mechanics, the several forces acting on the flow system can vary in magnitude. Adding to the difficulty of the problem is the evaluation of fluid properties such as density and viscosity, frictional loss determination for the multiphase mixture, and the calculation of phase velocities.

Although the literature contains various articles on different aspects of a pressure drop calculation problem in multiphase flow, the approaches are limited to the specific problem under study.[5-10] The models proposed by the investigators[5-10] are based on empirical correlations developed from laboratory studies and yielded reasonably accurate results. However, a general model that worked under all conditions of pipe inclinations and fluid mixtures was not developed.

Recently, neural networks (NN) have been employed in the petroleum industry[11,12], but their potential has not been fully investigated. In areas where a pattern exists between sets of data, a successful correlation can be developed with an artificial neural network (ANN). This pattern recognition capability of NN makes it a desirable tool to employ under a variety of conditions. When the data contain a relationship that is implicit in nature, a network such as Kohonen, Probabilistic, or Backpropagation may discover that relationship despite the complexity.

The purpose of this study is to develop and apply a new technology, Virtual Measurement in Pipes (VMP), to the pressure drop prediction under multiphase pipe flow conditions using neural networks.

Approach

A new method is introduced as a tool to investigate multiphase flow problems in wellbores. In this approach field and laboratory measurements were analyzed using artificial neural networks to detect the patterns and connections between the input data and the output pressure. The following section briefly describes the data used in this study and the features of the neural network.

Data from laboratory experiments and those from the field usually cover different ranges of input-output pressure. Two sets of data were used to develop the virtual measurement tool. The first set of data was from measurements taken at different wells and covered high pressure ranges between 600 psia and 12,000 psia. The second set of data was the laboratory pipe flow measurements that covered pressure ranges less than 100 psia.

Multiphase Flow Data.

Two different data sets were used in this study. The data for the first set consists of more than 200 measurements from different fields. Included in this set are data from the Texas Railroad Commission[10], Forties and Ekofisk Fields[6], and wells reported by Govier and Fogarasi.[10] The Railroad Commission well data contain wells with zero angle of inclination and the depths range from 7,237 ft. to 21,453 ft. The produced fluid contains mostly gas with gas-oil ratios above 10,000 SCF/STB and oil API gravity values higher than forty. Few wells were producing gas and only some produced water, with one well producing as high as 2,000 STB/D. The tubing sizes considered were between 1.995-in. and 3.958-in.

The data from Forties Field contains thirty-seven oil and gas rate measurements with no water in production tubing with inside diameters of 3.958-in. and 6.184-in. Well depths range from 7,093 ft. to 10,289 ft. and the average angle of inclination of a well varies between 0 degrees and 46.3 degrees from vertical. The fluid from wells contained modest amounts of gas and oil production rates were reported to be as high as 27,270 STB/D.

Fifty measurements from the Ekofisk field were taken from tubing internal diameters ranging from 2.764-in. to 4.892-in. with lengths ranging from 9,650 ft. to 14,330 ft. The average angles of inclinations of individual wells were between 0.0 degrees and 45.2 degrees from vertical. The light oil production rates ranged from 720 STB/D to 17,838 STB/D and the gas flow rates range from 1,672 MSCF/D to 55,700 MSCF/D.

The last portion of the data set consisted of 102 field measurements reported by Govier and Fogarasi. This section covers a wide range of production and well conditions from public files of the Energy Resources Conservation Board of Canada. The gas flow rates ranged from 674 to 27,400 MSCF/D and the oil rates ranged from seven to 1,660 STB/D. Well depths range from 3,678 ft. to 12,073 ft. with tubing size ranging between 1.995-in. and 4.404-in. Therefore, the combined data set covers a pipe size range between 1.995-in. and 6.184-in., and the inclination angle range between zero and 46.3 degrees from vertical.

The second data set was consisted of more than one thousand laboratory measurements conducted with a 30.5-ft. long and 1.5-in. diameter tubing.[13] Lube oil and kerosene were used with compressed air with angles of inclinations ranging between zero degrees and 90 degrees from horizontal. Pressure drop measurements were taken for upward and downward flow conditions. Due to the low pressure range employed in this experimental study, a separate network was designed.

Neural Network.

A three-layer feed forward back propagation neural network was designed to investigate the pressure drop prediction problems. The input layer consisted of pipe size and length, inlet and outlet temperatures, mass flow rates, fluid densities, inlet pressure, and angle of inclination. The output layer was the pressure at the outlet end of the tubing. This network was designed to determine outlet pressure with given inlet pressure in any pipe.

Figure 1 is a schematic diagram of the first NN designed for this task. The network consisted of twelve input neurons, twenty-six hidden neurons in the middle layer, and one output neuron. During the development stage, 90% of the data were used to train the network. The other 10% of the data were selected randomly and set aside to test the network's generalization capabilities. Once the network was trained and reached a stable state satisfactory to the investigators, the network was applied to the other 10% of the data. This process of development and testing were conducted using different training and testing sets. The results obtained in each case were equally accurate. This approach would verify the networks' generality and ensure its robustness.

A second NN similar to the first NN was designed using laboratory data. This network consisted of eleven input neurons with the elimination of a pipe diameter that was the same in all measurements. The middle layer had twenty-six hidden neurons. One output neuron was used for the output layer. A random selection of 10% of the data was also employed for the development of the second NN network. Different networks were generated with randomly selected training and test sets from the data. Similar results were obtained from all cases. As a final check, all data were used to predict outlet pressure with the NN and the results were compared against the laboratory measurements.

Discussion of Results

The pressure values predicted by the first NN for field data are shown in Figure 2. For a perfect match between predictions and measurements, all points should lie on the straight line. The pressure values for this network range from 653 psig to 11,890 psig and a very good agreement was observed between measured and the NN predicted values. Figure 3 compares the second NN predictions with the laboratory measured data. In the second network, the pressures range from 19.5 psig to 93.7 psig with good agreement between experimental work and predicted outlet pressure values. The mean and the standard deviation of the errors were 0.439 and 4.975 for the first network, and -0.214 and 3.256 for the second network, respectively. The statistical values were computed with equations listed in the Appendix. A correlation coefficient of 0.995 was obtained with predicted pressure values from the first network. The second network's correlation coefficient was 0.992. In both networks, the pressure predictions were based on the outlet pressure with given inlet pressure. The calculations in the reverse flow direction were also conducted, however, due to comparison purposes with a commercially available software with capability to calculate only in the flow direction, the network results for the runs conducted in the reverse direction are presented in this study.

To compare the NN predictions with existing correlations, the data from the first set were used as input and the pressure drop values were calculated with the commercially available software.[14] The computations were carried from the outlet end of the pipe and different correlation methods were employed. An arbitrary GOR value of 40,000 SCF/STB was used as the criterion to define wells as gas or oil producing, since the software package required the type of well as an input in selecting the correlation method. Five different correlations were used for 207 oil wells (with Hagedorn&Brown, Orkiszewski, Beggs&Brill, Dukler, and Aziz et al correlations) and twenty-four gas wells (with Fundamental Flow, Cullender&Smith, Hagedorn&Brown, Duns&Ros, and Gray correlations). Table 1 lists the mean, standard deviation, and the square of the correlation coefficient (r^2) for the deviations in predicted pressure values obtained with the commercially available software and the neural network. It was interesting that the r^2 value from the neural network is 0.995 and higher than all the oil well correlations, but lower than the gas correlations. However, the standard deviation and mean of the deviations are lowest from neural network predictions, showing a much better correlation. Another important observation in this comparison study is the consistently better performance of the same neural network compared to correlation models for oil and/or gas. Therefore, a single general model can be substituted for all the models.

Conclusions

1. A new neural network for pressure prediction in flowing wells under multiphase flow conditions was developed. The applicability of the network was successfully demonstrated. This approach introduces a new methodology for flowing bottom hole pressure prediction in wells.

2. The network can process the input data under various field conditions to detect the contribution of each input parameter.

3. Although the neural network was developed for the conditions defined by the data, the investigators believe that the new tool can be used with caution for conditions beyond the ranges considered in this study.

4. When the deviations in the predicted pressure values from the new neural network were compared with results from different established correlations, a mean value of 0.439 and a standard deviation value of 4.975 were observed. The mean values ranged from -16.121 to 1.175 for oil wells and from -0.889 to 5.808 for gas wells. The standard deviation values ranged from 19.226 to 27.676 for oil wells and from 6.068 to 20.621 for gas wells. The new NN predicts pressure values more closer to the measured values when compared to the correlations given for oil and gas wells in the commercially available software.

5. The new neural network provides an integrated approach for predicting pressure drop either in an oil or in a gas well by removing the limitation of the existing correlations applicable to only one type of well.

Nomenclature

e = Error, percent.
P = Pressure, psia.
s = Standard deviation.
N = Number of measurements.

Subscripts

avg = Average.
m = Measured.
p = Predicted.

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Appendix

Formulas used in the calculation of the statistical parameters are:

Average Mean Error:

$$e_{avg} = \frac{1}{N} \sum_{i=1}^{N} e_i$$

where the percent error is given as:

$$e_i = \frac{P_m - P_p}{P_m} \cdot 100$$

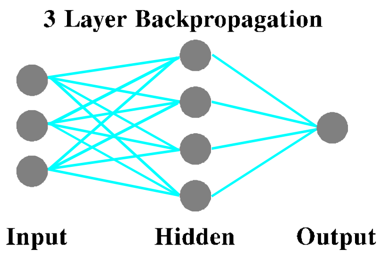
The standard deviations were calculated with:

$$s = \sqrt{\frac{\sum_{i=1}^{N} (e_i - e_{avg})^2}{N-1}}$$

TABLE 1 - COMPARISON OF CORRELATIONS

No.	Well Type	Correlation	Mean	Standard Deviation	r^2
1.	Oil	Hagedorn & Brown	-7.399	19.351	0.950
2.	Oil	Orkiszewski	-13.298	21.078	0.946
3.	Oil	Beggs & Brill	-16.121	19.226	0.953
4.	Oil	Dukler	1.175	27.676	0.852
5.	Oil	Aziz et al	-2.589	23.153	0.899
6.	Gas	Fundamental Flow	5.036	6.068	0.996
7.	Gas	Cullender & Smith	5.808	7.330	0.993
8.	Gas	Hagedorn & Brown	4.842	6.764	0.996
9.	Gas	Duns & Ros	-0.889	20.621	0.978
10.	Gas	Gray	5.314	6.424	0.996
11.	Oil & Gas	Neural Network	0.439	4.975	0.995

[redacted]



[redacted]

Figure 1. Schematics of the three-layer back propagation neural network.

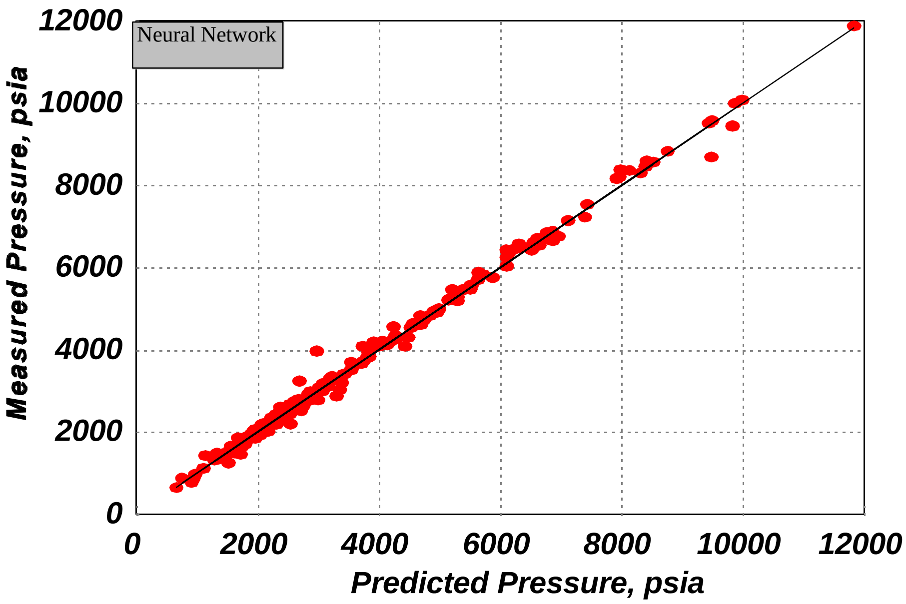


Figure 2. Performance of neural network using field data.

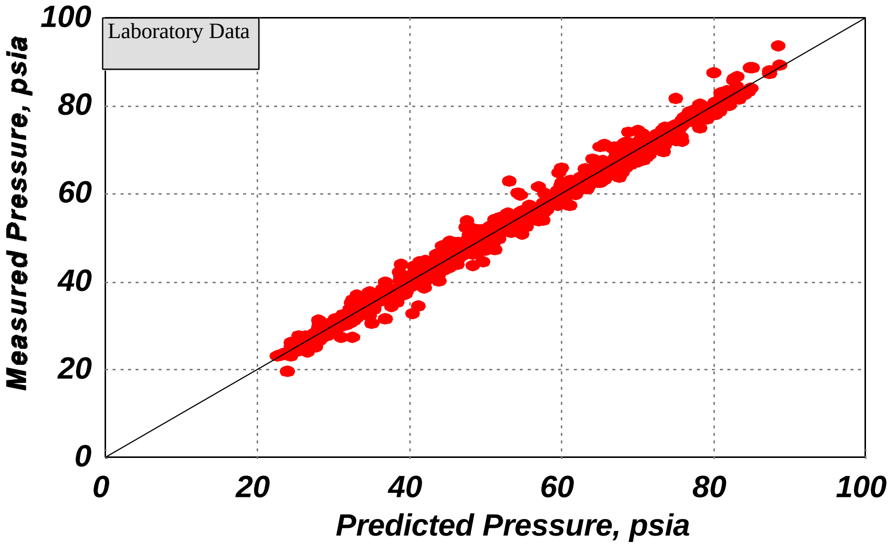


Figure 3. Performance of neural network using laboratory data.