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Virtual Measurement in Pipes, Part 2: Liquid Holdup and Flow Pattern Correlations

J. Ternyik, IV, SPE, H.I. Bilgesu, SPE, S. Mohaghegh, SPE, West Virginia U.

Abstract

The prediction of liquid holdup and multiphase flow regimes present in a well or pipeline is very important to the petroleum industry. Liquid holdup, defined as the fraction of pipe occupied by liquid, and flow regimes must be predicted to design separation equipment and slug catchers in pipeline operations properly. It is also important when designing gas storage fields in depleted oil reservoirs.

A new methodology was developed to model multiphase flow conditions for pipelines and wellbores using only known surface data. This methodology, which has been named Virtual Measurement in Pipes (VMP), incorporates an innovative use of information technology and computational intelligence, to address the development of tools for the engineer to use in the design process for a variety of conditions. Artificial neural networks (ANN) were used to develop a Virtual Measurement Tool to survey the liquid holdup and flow regimes in nonspecific multiphase flow systems using readily available data.

The VMP methodology was tested for validity by comparing virtually measured values with published measurements. As a result, the method proved to be an accurate virtual measuring tool to predict liquid holdup and flow regimes in multiphase flowing pipelines and wellbores. The VMP methodology also demonstrated an enhancement to existing industry recognized correlations.

Introduction

Flow of gas and liquid occurs frequently in pipelines and wellbores where the accurate calculation of a pressure drop is of considerable interest to the petroleum industry. Similar conditions exist in the chemical and nuclear industries where two-phase mixtures coexist. In the petroleum sector, gas-liquid mixtures are transported over long distances in a common line under large pressure drops which influence the design of the system. Other important areas of application can be cited as gas lift operations and wellhead gathering systems. Practically all oilwell production design involves evaluation of flow lines under two-phase flow conditions. However, the uncertainties in flow regime determination greatly affect the pressure drop predictions. A method is desired for accurate calculation of pressure losses.

Pressure losses in two-phase, gas-liquid flow are different from single-phase flow. An interface exits in most cases and gas slips past the liquid with a surface of varying degrees of roughness depending on the flow pattern. Each phase flows through a smaller area than if it flows alone causing high pressure losses when compared to single-phase flow. Additionally, this segregated flow changes at any point along the flow path during the fluctuating flows. Under the conditions of distributed phases, prediction of fluid mixture properties like density and viscosity becomes a challenge for the design engineer.

The density and viscosity along with the velocity are important terms in the determination of pressure losses in any pipe system. Several correlations are proposed to define the holdup and flow patterns for horizontal, vertical, and inclined pipes.[1-5] In general, these correlations are based on experimental work conducted under specific conditions such as a constant pipe diameter.

The application of artificial neural networks in the petroleum industry is recent and its potential is not fully investigated. This technology is applicable in many areas where an existing pattern is not obvious to the naked eye of the researcher as is the case of log evaluations.[6] Complex patterns and relationships in data, such as holdup and flow pattern, can be established through an artificial neural network.

Approach

A new methodology is introduced to investigate the holdup and flow pattern determination problem in pipes under multiphase conditions. This approach uses the measured data to determine the relationship between input and output parameters. The Virtual Measurement in Pipes (VMP) tool utilizes the pattern recognition capabilities of an artificial neural network.

Data from Mukherjee's[7] Ph.D. Dissertation was used in the present study. The experimental data was selected due to extensively wide coverage of inclination angles and flow patterns. Kerosene, lube oil, and compressed air were used in Mukherjee's work to measure pressure drop, holdup and flow patterns in a 1.5-in. pipe. Mukherjee conducted all runs with pressure ranges below 100 psig. and took measurements for upward and downward flow at an angle of inclinations ranging from zero degrees and 90 degrees from horizontal.

Different neural networks were developed for holdup and flow pattern predictions. A three-layer back propagation neural network was used in all cases due to its success in predicting the pressure loss in pipes[8] and the ability to generalize with good accuracy on a variety of problems. In the standard type of back propagation paradigms, every layer is connected to the immediate previous layer. With sufficient number of hidden neurons in the middle, a three-layer network was determined to be suitable for the problem investigated.

Holdup.

The first neural network was developed to correlate holdup input data with the measured values. Initially, a Kohonen type network was designed to classify the four different correlations for flow patterns with all input data. The Kohonen network, which is a self organizing, unsupervised network, has the ability to learn without the knowledge of correct outputs and it uses two layers, namely, input and output. The resulting classifications from the output layer in binary form were used as data in the design of the back propagation neural network. Preprocessing of data was necessary to identify the contribution of input data to holdup predictions. The three-layer back propagation neural network was designed with eleven input parameters consisting of angles of inclination, oil and gas flow rates, oil specific gravity, inlet and outlet pressures, inlet temperature, and four binary data, each representing one flow pattern from the Kohonen model output. The hidden layer in the final design was consisted of thirty-seven neurons and the holdup was the output neuron. During the development stage, 10% of the data set was randomly selected and set aside. The remaining 90% of data were used to train the network. Different combinations of learning rates and momentums were studied to design the optimum neural network. At the end of each training, determined by the stable state of the network, the developed network was applied to the test set.

Flow Pattern

The neural network developed in predicting the flow patterns was based on a design similar to the holdup network. However, the holdup was used as an input and binary data from the Kohonen network was unnecessary. The three-layer back propagation neural network was designed with eight input, thirty-seven hidden and four output neurons. Gas and liquid flow rates, inlet and outlet pressures, liquid specific gravity, average temperature, angle of inclination, and holdup were used as input. The output layer was consisted of slug, bubble, annular mist, and stratified flow patterns.

Discussion of Results

Figure 1 shows the log-log plot of all the data points used in this study. Superficial gas velocity in ft/sec is plotted on the x-axis for values between 10^{-3} and 10^{3} ft/sec. The corresponding superficial liquid velocities are plotted on the y-axis for values between 0.01 and 100 ft/sec. The experimental data covered four different flow patterns and the location of each point varied with angle of inclination. No distinguishable regions were observed for any type of flow pattern. Further complicating the problem is the existence of different flow patterns under the same superficial velocity conditions.

Figure 2 shows the comparison of predicted and measured holdup values from Mukherjee's study. The same comparison is shown in Figure 3 for the work done with the new NN. The results from both studies show good agreements. However, the square of the correlation coefficient was 0.945 from the NN and this value was higher than 0.904 obtained from Mukherjee's correlation. In this study, inlet and outlet pressures were used in the input layer and both values may not be available often. Under the conditions where one pressure value is not measured, a neural network can be designed to predict the required pressures before running the neural network for holdup.

Figure 4 shows the NN predicted flow patterns as a pie-chart. A similar chart is presented in Figure 5 for the results of the work done by Mukherjee. Each pie shows the percent of data predicted as slug, bubble, annular mist, and stratified for one category of data. The flow patterns were correctly predicted for 93.3, 82.8, 87.0, and 89.2 percent of data for slug, bubble, annular mist, and stratified flow, respectively. Among the four flow patterns the highest success was achieved in the slug flow case with 93.3% of correct pattern predictions. This prediction compares favorably with Mukherjee's prediction of 86.4%. Although the pattern prediction for bubble flow was lowest among the four with a value of 82.8%, this is more than a twofold improvement over the 40.2% correct prediction reported by Mukherjee. Similar conditions were observed for results with annular mist and stratified flow data.

It is interesting that annular mist and bubble flow patterns were easily distinguishable in correlations presented by Mukherjee and NN predictions. In both predictions the bubble flow was not mistaken for annular mist flow and vice versa. This is expected since laboratory observations verify the existing of a slug or intermittent flow zones between bubble and annular mist flow regions. Another improvement observed from NN predictions was the correct identification of the interface between bubble and stratified flow which varied linearly with superficial gas velocity. As a result the data from stratified flow conditions were not mistaken for bubble flow by the developed NN. Due to variations in the location of the interface between bubble and slug, and also between annular mist and slug flow regions, under changing degrees of pipe inclinations, bubble and annular mist flow predictions had the most errors in pattern predictions.

Under the bubble flow conditions 15.3% of data were incorrectly predicted as slug flow, but only 3.6% of slug flow data were mistaken for bubble flow. Similarly, 12.0% of data from annular flow conditions were incorrectly predicted as slug flow as compared to 1.3% slug flow data mistaken for annular mist flow. This suggests that the input pattern recognized by the NN under slug flow conditions are more related and less complex than the pattern existing for the bubble and annular mist flows.

Conclusions

1. A new tool was developed and successfully applied to holdup and flow pattern prediction in pipes under the various angles of inclinations. The network recognized the relation between complex patterns by processing input data.

2. The developed NN was based on experimental data and limited to a 1.5-in. pipe and low operating pressures. However, a similar network can be developed and applied to pipes with larger diameters and pressure ranges if data is available.

3. Holdup values predicted by the NN had a value of 0.945 for the square of the correlation coefficient. This showed an improved correlation when compared to the previous investigator's result of 0.904.

4. The NN developed for the flow pattern prediction was based on slug, bubble, annular mist, and stratified flows. The flow pattern predictions were very successful with correct values ranging between 82.8% for bubble flow and 93.3% for slug flow.

References

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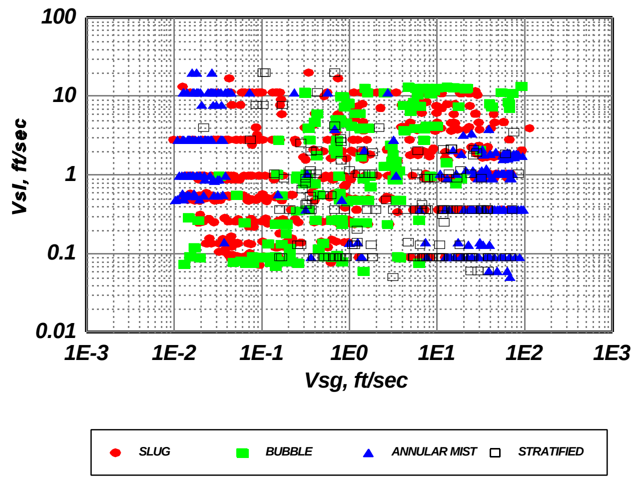

Fig. 1 - Location of experimentally measured four flow patterns on the gas-liquid superficial velocity cross-plot.

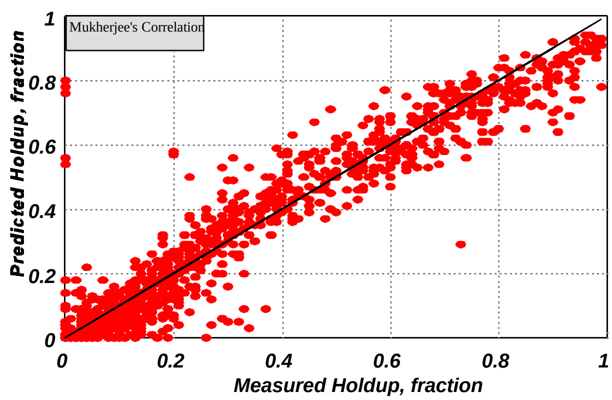

Fig. 2 - Comparison of predicted versus measured holdup values from Mukherjee's work.

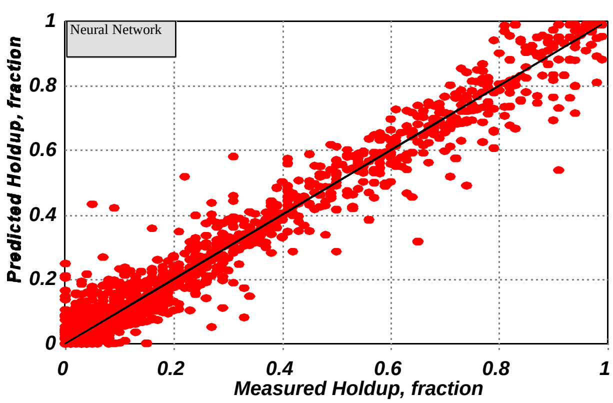

Fig. 3 - Comparison of NN predicted holdup values with experimental data from Mukherjee.

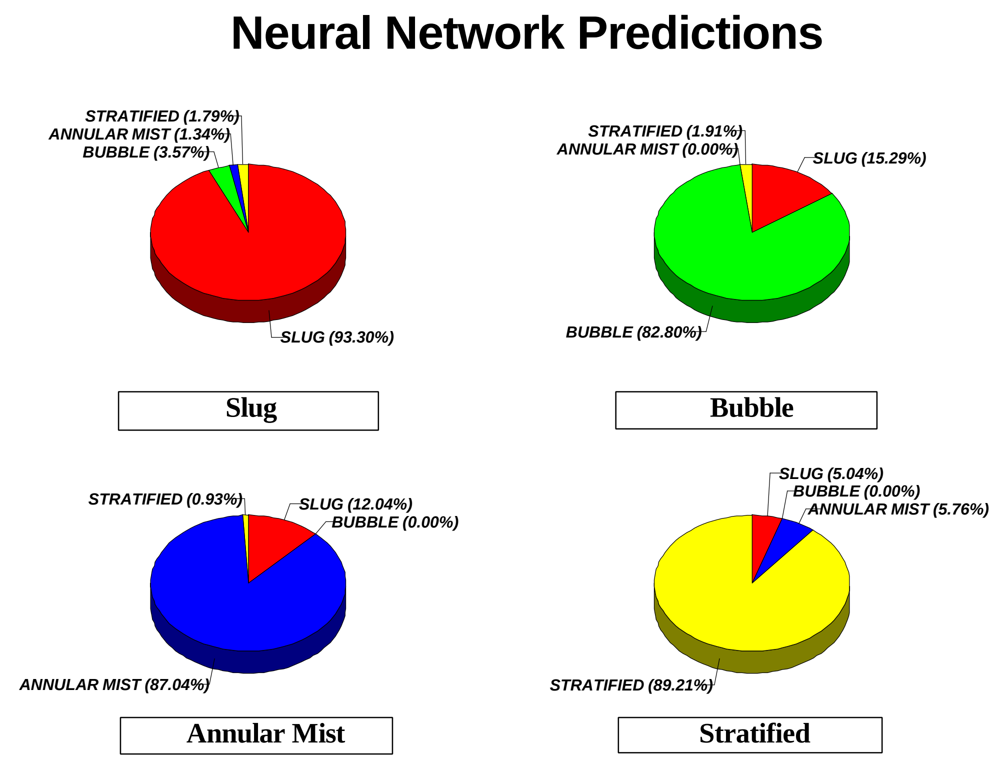

Fig. 4 - Percent of flow patterns predicted by the NN for slug, bubble, annular mist, and stratified flow.

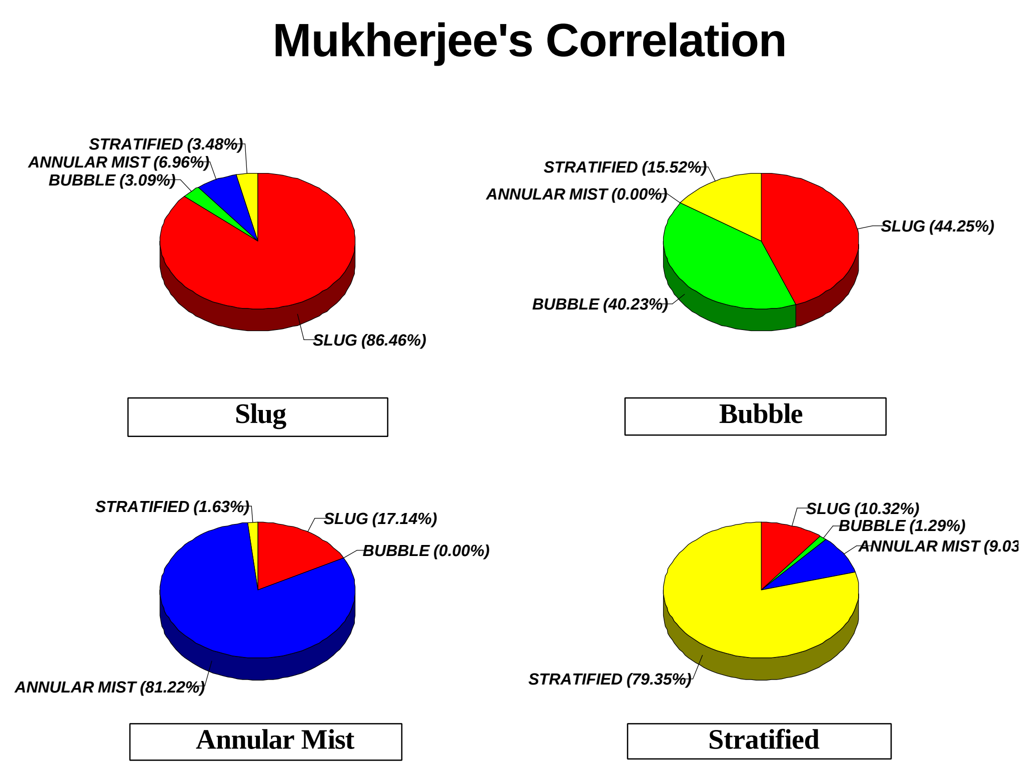

Fig. 5 - Percent of flow patterns predicted in Mukherjee's work for slug, bubble, annular mist, and stratified flow.