Pressure Loss Estimation of Three-Phase Flow in Inclined Annuli for Underbalanced Drilling Condition using Artificial Intelligence

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Abstract

Underbalanced drilling as multiphase flow is done in oil drilling operation in low pressure reservoir or highly depleted mature reservoir. Correct determination of the pressure loss of three phase fluids in drilling annulus is essential in determination of hydraulic horsepower requirements during drilling operations. In this paper the pressure loss of solid-gas-liquid three-phase fluids flow in inclined annulus was estimated using artificial neural network (ANN). Experimental data which are available in the literature were used for design of ANN. Pressure loss as output of ANN, was estimated from five effective parameters as inputs of ANN including gas and liquid superficial velocities, the inclination from horizontal, rate of penetration (ROP), pipe rotation speed (RPM). The correlation coefficient between predicted and experimental value for train and test data is 0.998 and 0.997 respectively.The root mean square error (RMS) and average absolute percent relative error (AAPE) for train data are 0.0082 and 2.77% and for test data, they are 0.0108 and 3.68 % respectively. The reliable results showed the high ability of artificial neural network for estimating pressure loss of three phase flow in annulus.

Keywords

Underbalanced drilling;
Pressure loss;
Three-phase flow;
ANN;
Annulus.

1. Introduction

Underbalanced drilling (UBD) is used in development of low-pressure reservoir or highly depleted mature reservoir because of minimizing of formation damage and lost circulation, increasing penetration rate, and extending bit life. There are many techniques for underbalanced drilling including gas, foam, gasified-liquid and liquid underbalanced drilling. Gasified fluid drilling has many applications, because of its wide adjustable equivalent circulating density. The introduction of gaseous phase to the drilling fluid circulating system complicates prediction of drilling hydraulics and solids transport. The proper underbalanced drilling is determined by suitable design of hydraulics requirements. The underbalanced drilling with

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gasified-liquid as three-phase flow is more complicated with respect to single-phase fluid, because of the complicated characteristics of multiphase fluid flow [1, 2]. Therefore proper design of hydraulics parameters of aerated mud flows in order to estimate accurately desired bottom hole pressure and to optimize fluid flow rates is necessary.

Extensive theoretical and experimental studies of two-phase flow through pipes have been performed. These studies are general models and mechanistic models. Previous developed models for two-phase fluid flow which named general models, were independent from flow pattern description. The general model considered two-phase fluid flow as single phase flow or as a separated two-phase flow [3, 4].

The studies that the researchers firstly determine the flow patterns are mechanistic models. The main step in mechanistic modeling is the accurate determination of the flow patterns, properly. Many studies carried out with the aim of estimating the flow patterns of two-phase fluids in pipes.The main mechanistic models are based on the presented flow patterns [5, 6, 7]. Some main studies in two-phase fluids flowing through annulus were conducted by many researchers [2, 8-14]. There are less theoretical and experimental studies on particles transport in solid-gas-liquid multiphase flow through pipes and annuli [15-20].

Most of the mentioned models (correlations and mechanistic models) consider either the two-phase flow as a single-phase fluid flow or they have been applied to a special range of conditions such as well geometry and inclination and flow condition. Such models cannot be generalized due to the nature of a UBD. There is not an analytical solution for multiphase pressure loss estimation. So it is crucial to develop a simple and proper method to explain the behavior of multiphase fluid flow through annuli in horizontal and inclined wells under UBD condition.

Artificial neural network (ANN) has been motivated right from its inception by the recognition that the human brain computes in an entirely different way from the conventional digital computer [21]. It can be used to model various complex and nonlinear problems in addition to other statistical methods [22- 24]. ANN has been used in the multiphase flow fieldwith acceptable results compared with the conventional methods such as correlations and mechanistic models [26-29]. The aim of this study is to estimate pressure loss of three phase (solid- liquid- gas) flow through inclined annuli using simple and reliable ANN model that it has not been done in previous works.

2. Artificial Neural Network (ANN)

ANNs are a wide class of flexible nonlinear regression models, data reduction models, and nonlinear dynamical systems. They consist of an often large number of neurons, i.e. simple linear or nonlinear computing elements, interconnected in often complex ways and often organized into layers. ANNs mimic the human mind neural network using conventional digital computer [21, 30]. A typical neuron structure is shown in Fig. 1. ANN has a multilayer structure including input layer (p), middle layer (hidden layer) with activation function (Fig. 2) and output layer (a). The middle layer is built upon many simple nonlinear functions that play the role of neurons in a biological system [31].

There are different types of neural networks that differ in the network architecture and neuron structure such as back propagation neural network (BPNN) and radial basis function network. The feed-forward neural networks with back propagation (BP) learning are very powerful in function optimization modeling [25, 32, 33]. Backpropagation neural networks are recognized for their prediction capabilities and ability to generalize well on a wide variety of problems. These models are supervised networks, on the other words, trained with both inputs and target outputs. During training, the network tries to match the outputs with the desired target values. BPNN technique has a main disadvantageas over fitting phenomenon. Early stopping and automated Bayesian regularization methods are themost common methodsto avoid over fitting [31]. In this study, automated Bayesian regularization method [25] was used for avoiding over fitting problem.

3. Pressure Loss Prediction of Three-Phase Flow using ANN

In this paper, a BPNN code with automated Bayesian regularization algorithm using MATLAB software was used for pressure loss prediction.

124 three phase flow data sets including cutting-gas-water flow for three degree from horizontal (0, 45 and 77.5) eccentric annulus (0.623 eccentricity) extracted from literature were used to train and test the ANN model. The geometry of annulusis a test section with approximately 21 ft. long with 2.91 in (inner diameter) transparent acrylic casing with a 1.86 in (outer diameter) inner drill pipe. The inner pipe is attached to a variable speed motor, which enables the rotation of the drill pipe at variable speed (Fig. 3) [11, 19].

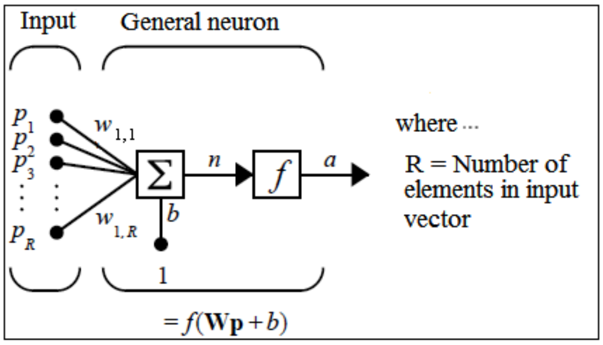

Figure 1. A typical neuron [31].

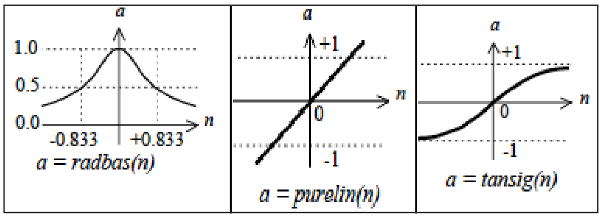

Figure 2. Three examples of activation functions [31].

Five variable parameters including gas (air) and liquid (water) superficial velocity (V_{SG} and V_{SL}), inclination from horizontal (θ), rate of penetration (ROP) that relate to solid phase, pipe rotation speed(RPM) were used as inputs of the network and pressure loss (dP/dL) in eccentric annulus was used as output of network (Table 1). The characteristics of water and air (rheological parameters and density), geometry of annulusand cuttings characteristics (particle diameter, 0.079 in; cutting density, 23.05 ppg; cutting bed porosity, 36%) in all tests were considered constant [11]. Eccentric ratio in all tests was 0.623. So they are

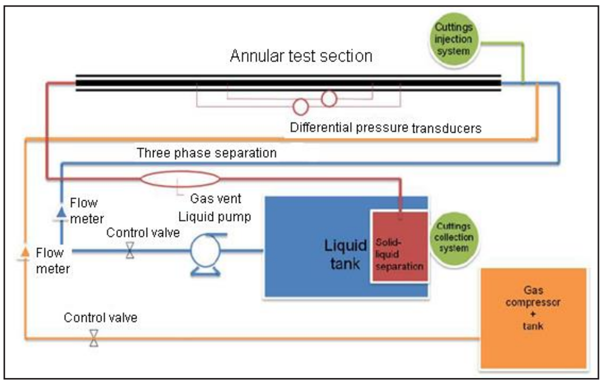

Figure 3. Schematic of experimental setup [11, 19].

Table 1. The range of used data .

Parameter	Minimum	Maximum
V_{SG} (ft/s)	0.132	33.78
V_{SL} (ft/s)	1.79	6.005
θ (degree)	0	77.5
ROP (ft/h)	60	120
RPM (1/min)	0	120
dP/dL (psi/ft)	0.042	0.626

not considered as BPNN inputs. The superficial velocities of phases are calculated as:

$$V_{SL} = \frac{Q_L}{A} \tag{1}$$

$$V_{SG} = \frac{Q_G}{A} \tag{2}$$

where, Q_G, Q_L are gas and liquid flow rates respectively and A is the cross sectional area of annuli. The minimum and maximum of used data is in Table 1.

For better recognition of parameters used by BPNN, the inputs and output data were normalized intherange of [-1, 1] using Eq. (3),

$$p_n = 2\frac{p - p_{\min}}{p_{\max} - p_{\min}} - 1 \tag{3}$$

where, p_n is the normalized parameter, p denotes the actual parameter, p_{min} represents a minimum of the actual parameters and p_{max} stands for a maximum of the actual parameters.

99 data sets out of 124 data sets were selected as train data and the rest were considered for test purposes.

A single hidden layer of the backpropagation has been proven to be capable of providing accurate approximations to any continuous function with sufficient hidden units [32]. Fletcher and Goss [34] suggested that the appropriate number of nodes in a hidden layer ranges from ($2\sqrt{n}$+ m) to (2n + 1), where n is the number of input nodes and m is the number of output nodes.

Several architectures (varied numbers of neurons in hidden layer according to trial and error) with automated Bayesian regularization training function (trainbr) were applied to prevent from over fitting problem, were tried to predict pressure losses using BPNN.

Three criteria [25] were used to evaluate the effectiveness of each network and its ability to make accurate predictions are; the root mean square error (RMS), average absolute percent relative error (AAPE) and the correlation coefficient (R). The RMS measures the data dispersion around zero deviation, given by:

$$RMS = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{N}} \quad (4)$$

$$AAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{(y_i - \hat{y}_i)}{y_i}\right| \quad (5)$$

$$R = \sqrt{1 - \frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{N} y_i^2 - \frac{\sum_{i=1}^{N}\hat{y}_i^2}{N}}} \quad (6)$$

where, y_i is the measured value, $\hat{y}_i$ denotes the predicted value, and N stands for the number of samples.

Table 2 shows results obtained from different structure of ANN. According to Table 2, the appropriate number (10 neurons) of hidden layer neurons was chosen.

The optimum BPNN structure is 5–10–1 (5 inputs, 10 hidden neurons with log-sigmoid activation function, 1 output neuron with linear activation function) with automated Bayesian regularization training function (trainbr) (Fig. 4).

4. Results and discussion

The pressure loss of three-phase flow in eccentric inclined annulus was estimated using designed simple and proper BPNN. This method can indicate relation between the effective operational parameters and pressure loss. In this paper five variable inputs (V_{SL}, V_{SG}, ROP, RPM, θ) were used for pressure loss (dP/dL) estimation. Other parameters were constant in all tests.

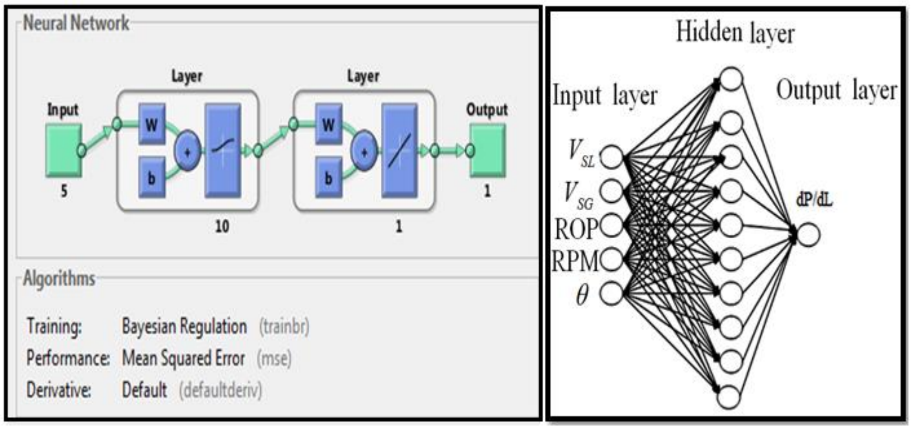

Figure 4. Schematic of the pressure loss neural network.

Table 2. The results of different ANN structure.

Neurons in the hidden layer	Training set R	Training set RMS (psi/ft)	Training set AAPE%	Test set R	Test set RMS (psi/ft)	Test set AAPE%
6	0.997	0.011	4.243	0.992	0.019	7.179
7	0.998	0.009	3.498	0.992	0.019	6.000
8	0.998	0.008	3.298	0.996	0.013	4.932
9	0.998	0.008	2.889	0.997	0.012	4.048
10	0.998	0.008	2.770	0.997	0.011	3.688
11	0.998	0.008	2.887	0.997	0.012	4.123
12	0.998	0.009	2.834	0.996	0.013	4.373

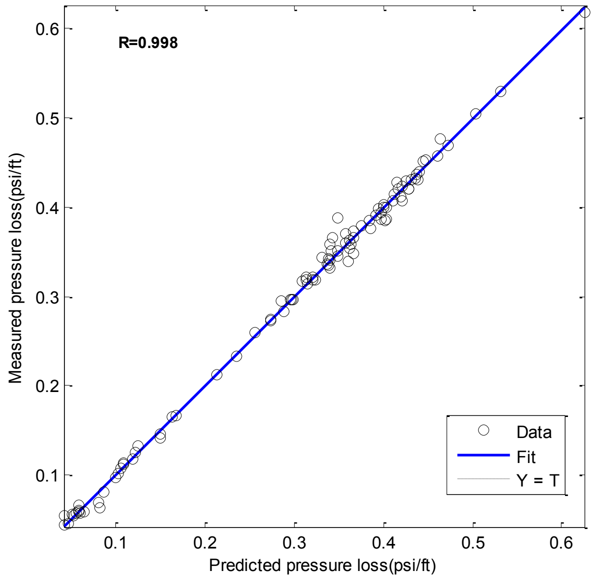

Figure 5. BPNN pressure loss versus measured pressure loss for the training data.

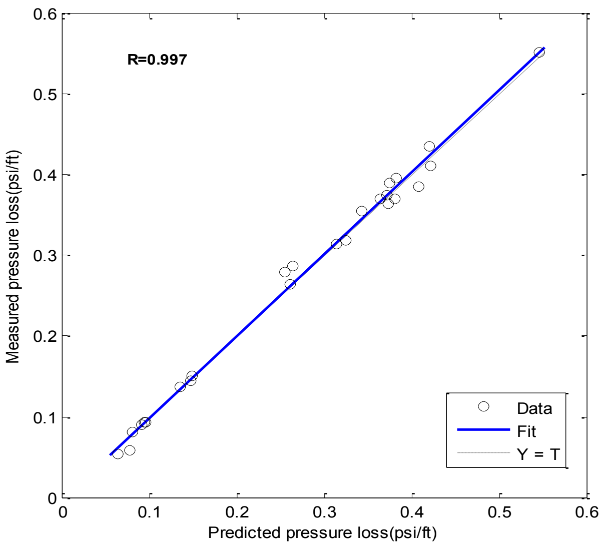

Figure 6. BPNN pressure loss versus measured pressure loss for the test data.

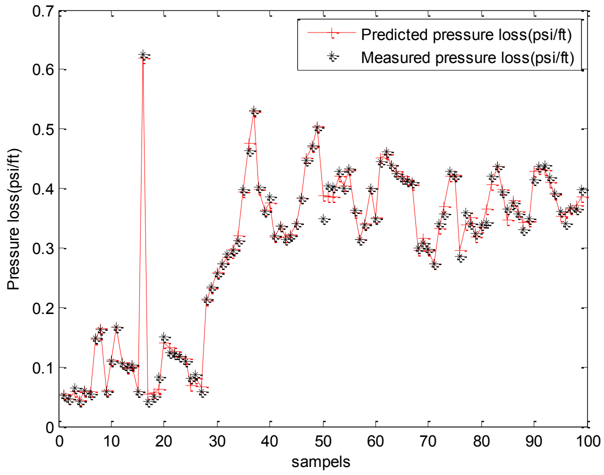

Figure 7. Predicted pressure loss versus measured pressure loss for train samples.

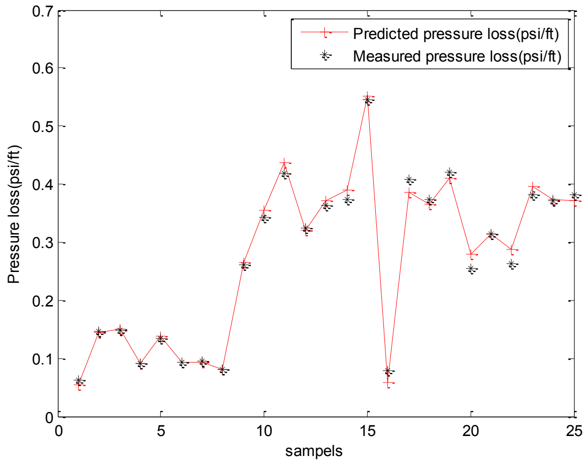

Figure 8. Predicted pressure loss versus measured pressure loss for test samples.

For this purpose, 99 samples of 124 samples were randomly used to train of the network and 25 samples were used for testing BPNN.

The correlation coefficient (R), AAPE and RMS were used for comparison results of ANN. Figure 5 shows the estimated (predicted) pressure loss versus the experimental (measured) values for the training data. The correlation coefficient (R) is 0.998 with an RMS and AAPE value of 0.0082 and 2.77%. These results show correct training of BPNN. Testing and evaluation of BPNN was done using test data. The comparison of the predicted pressure loss versus the measured (experimental) pressure loss for test data is shown in Figure 6. The correlation coefficient (R) is 0.997 and the RMS and AAPE are 0.0108 and 3.68 %, respectively. These results show high ability of simple BPNN method for pressure loss estimation of three phase flows.

5. Conclusions

This study proposed a BPNN model for pressure lossestimation of three phase flow in inclined eccentric annulus from affected parameters including, liquid and gas superficial velocities (V_{SL} and V_{SG}), pipe rotation speed (RPM), rate of penetration (ROP) and inclination of annulus from horizontal (θ).Ten neurons with logsig activation function in hidden layer of BPNN was selected by trial and error. The correlation coefficient of train and test data is 0.998 and 0.997, respectively and the RMS and AAPE of train data are 0.0082 and 2.77% and for test data, they are 0.0108 and 3.68 %, respectively. The results showed that the developed model provides predictions in acceptable agreement with target data. This model is simple and reliable according to its independence from flow pattern determination, non-complexity and high accuracy in estimation of pressure loss of three phase flow.

Nomenclature

A	Cross sectional area of annuli (in^2)
AAPE	Average absolute percent relative error (%)
ANN	Artificial neural network (-)
BPNN	Back propagation neural network
dP/dL	Pressure loss (psi/ft)
N	Number of samples (–)
Q_G	Gas flow rate (scf)
Q_L	Liquid flow rate (gpm)
R	Correlation coefficient (-)
RMS	Root mean squared error (-)
ROP	Rate of penetration (ft/h)
RPM	pipe rotation speed (1/min)
V_{SL}	Liquid superficial velocity (ft/s)
V_{SG}	Gas superficial velocity (ft/s)
θ	Inclination from horizontal (degree)

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