Journal of Applied Fluid Mechanics, Vol. 9, No. 5, pp. 2469-2474, 2016.
Available online at www.jafmonline.net, ISSN 1735-3572, EISSN 1735-3645.
DOI: 10.18869/acadpub.jafm.68.236.24072

Prediction of Pressure Drop for Oil–Water Flow in Horizontal Pipes using an Artificial Neural Network System

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(Received September 19, 2014; accepted December 6, 2015)

ABSTRACT

In this study, pressure drop for oil–water flow in horizontal pipes is represented by using artificial neural network (ANN). Results were compared with Al-Wahaibi correlation and Two-fluid model. This research has used a multilayer feed forward network with Levenberg Marquardt back propagation training for prediction of pressure drop. Original data were divided into two parts where 80% of data was used as training data and remaining 20% of data was used for testing. In this method inputs are oil superficial velocity, water superficial velocity, ratio of density, ratio of viscosity, diameter of pipe and roughness of the pipe wall. The number of neurons is set on four. The feasibility of ANN, Al-Wahaibi correlation and Two-fluid model has been tested against 11 pressure drop data sources. The average absolute percent error of Al-Wahaibi correlation and two-fluid model are 12.73 and 15.84 while this average for the same systems using neural network is only 6.36.so the ANN is in good agreement with experimental data.

Keywords: Oil–water flow; Neural network; Pressure drop prediction; Separated flow.

NOMENCLATURE

A_w	cross sectional areas of the water	U_m	the mixture velocity
A_o	cross sectional areas of the oil		
D	pipe diameter	ε	wall roughness
$\frac{dp}{dz}$	Pressure drop	τ_i	interfacial shear stresses
Re_m	Reynolds number	τ_o	Oil shear stresses
S_o	wall wetted perimeter of the oil	τ_w	water shear stresses
S_w	wall wetted perimeter of the water	ρ_m	mixture density
S_i	interfacial length		

1. INTRODUCTION

Oil-water flow is commonly encountered in the petroleum and chemical industry. Pressure drop is a significant parameter in the design of an efficient transportation system and is greatly affected by fluid properties, and flow patterns. Several attempts have been made in predicting the pressure drop of liquid-liquid flow in the last six decade years, and in most of the cases, theories based on gas-liquid flows have been used in liquid-liquid flows (Brauner, 2001; Brauner, 1992).

When a phase of oil-water was in laminar flow and the other was in turbulent flow, Charles and Lilleleht (Charles, 1966), and Stapelberg and Mewes (Stapelberg, 1994)applied empirical parameter, suggested by Lockhart and Martinelli (Lockhart, 1949) for gas–liquid flow in pipelines to predict pressure drop data in the stratified flow. The correlation was not able to represent the pressure drop for oil-water flow. Stapelberg and Mewes (1994) suggested that pipe diameter obviously must be considered for predicting pressure drop, and a single model is not adequate to correlate the data in all the flow regimes of oil-water flow. In recent papers, Angeli and Hewitt (1998), Chakrabarti *et al*. (2005), Rodriguez and Oliemans (2006), and

Table 1 Database for frictional pressure drop in separated horizontal oil–water flow

Source	No. of data points	D (mm)	Pipe material	$\frac{\mu_o}{\mu_w}$	$\frac{\rho_o}{\rho_w}$	Pipe roughness (mm)
Valle and Kvandal (1995)	10	37.5	Glass	2.3	0.794	0.01
Nädler and Mewes (1997)	27	59	Perspex	28	0.841	0.01
Angeli and Hewitt (1998)	26	24	Acrylic	1.6	0.801	0.01
Angeli and Hewitt (19980	33	24.3	St. steel	1.6	0.801	0.07
Elseth(2001)	55	56.3	Acrylic	1.64	0.79	0.01
Chakrabarti *et al*. (2005)	67	25.4	Acrylic	1.3	0.787	0.01
Rodriguez and Oliemans (2006)	23	82.8	St. steel	7.5	0.783	0.07
Al-Wahaibi *et al*. (2007)	37	14	Acrylic	5.5	0.828	0.01
Yiping *et al*. (2005)	33	26.1	St. steel	3.5	0.840	0.045
Al-Yaari *et al*. (2005)	32	25.4	Acrylic	1.57	0.780	0.01
Yousuf (2011)	28	25.4	Acrylic	12	0.875	0.01

Yiping *et al*. (2008) used the two-fluid model to obtain the pressure drop using plane and curve interface. Large discrepancies were observed between the measured and predicted values especially in dual continuous flow.

Neural networks are currently being extensively applied in many fields of engineering and science (Kalra *et al*., 2005; Sözen and Arcakliogˇlu, 2005; Abbassi and Bahar, 2005; Yang *et al*., 2005; Peisheng *et al*., 2005; Yagci *et al*., 2005; Rezzi *et al*., 2005; Madan, 2005). The major reason for this rapid growth and diverse application of neural networks is their ability to estimate virtually any function in a stable and efficient way. Hence, they create a platform on which different models can be constructed. It is expected that a neural network approach would offer a helpful and beneficial new solution to solve this particular problem.

In this study, Pressure drop data in different experimental conditions is used to predict pressure drop of oil–water flow in horizontal pipes in a simpler and more reliable method that called neural network. Neural network with four neurons is used because of its more simplicity and accuracy compared with other existed correlation. In this method experimental data is divided into two parts. The first part which includes 80% of data is used for training of neural network. The second part including 20% of data is used for testing. Finally the obtained data of this method is compared with Al-Wahaibi correlation (Talal Al-Wahaibi, 2012) and Two-fluid model that leads to less deviation.

2. MATERIAL AND METHODS

2.1 Material

Pressure drop measurements corresponding to 370 experimental points obtained from the literature at different superficial oil velocity, superficial water velocity, ratio of density, ratio of viscosity, diameter of pipe and roughness of the pipe wall for separated oil–water flow in horizontal pipes were employed in this study. Table 1 summarized the range of the selected data. These include the data published by Valle and Kvandal (1995), Nadler and Mewes (1997), Angeli and Hewitt (1998), Elseth (2001), Chakrabarti *et al*. (2005), Rodriguez and Oliemans (2006), Al-Wahaibi *et al*. (2007), Yiping *et al*. (2008), Al-Yaari *et al*. (2009), and Yousuf (2010).

2.2. Artificial Neural Network

Artificial neural networks (ANNs) are highly flexible mathematical constructs that have been inspired by the workings of the biological nervous system. ANNs have a natural tendency for storing experiential knowledge and making it available for use (Haykin, 1999). ANNs can simply be viewed as general nonlinear models which have the ability to encapsulate the underlying relationship that exists between a series of inputs and outputs of a system.

There are many different ANN structures like MLP (multi layer perception), RNN (recurrent neural network) and RBF (radial basis function). Each of these structures has been used for the modeling different case studies (Haykin, 1999).

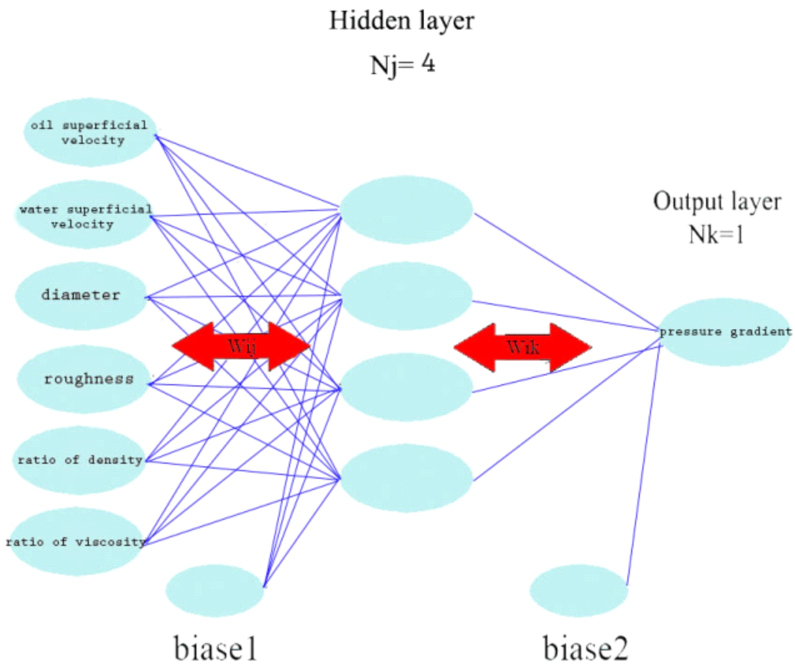

Fig. 1. Feedforward neural networks used to represent pressure drop.

In this research a multilayer Feed forward neural network (FFNN), which is undoubtedly the most common neural network structure used in engineering applications, have been used. It has been shown that a three-layer (input-hidden-output) FFNN can represent any function provided that sufficient number of neurons are present (Cybenko, 1989). The Feed forward neural networks that have been used in this examination are presented in Fig. 1.

Feed forward describes how this neural network processes and recalls patterns. In a feed forward neural network, neurons are only connected foreword. Each layer of the neural network includes connections to the next layer, but there are no connections back.

The input layer receives the process inputs and fans out this information to all functional neurons of the hidden layer. Each neuron of the hidden layer essentially accomplishes two works: (1) a weighted summation of all process inputs; and (2) a non-linear transformation, via a neuron transfer function, of the weighted summation to produce the output of each neuron of the hidden layer which then serves as inputs to the neurons of the output layer. The output layer performs the same task as the neurons of the second layer to produce the final output of the FFNN. The typical transfer functions that are used in the hidden and output layers are linear, sigmoid or hyperbolic tangent. Fig. 2 shows the general topology of a typical neuron.

The input and output to the FFNN are usually scaled between 0.1 and 0.9 as follows:

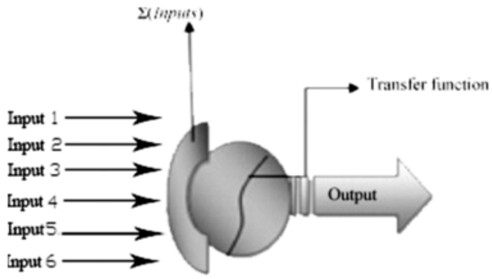

Fig. 2. General topology of a neuron.

$$(\text{Scaled})_{\text{value}} = \frac{(\text{Actual})_{\text{value}} - \text{minimum}_{(\text{Actual value})}}{\text{maximum}_{(\text{Actual value})} - \text{minimum}_{(\text{Actual value})}} \times 0.8 + 0.1 \quad (1)$$

Original data is classified into two groups. Usually about 20% of data is selected as test data and 80% of data is used for training. Here “back propagation” method with Levenberg Marquardt algorithm is used for training of inputs. Back propagation is a very common method for training multilayered feed forward networks and Levenberg Marquardt generally is the fastest and default algorithm for FFNN. Before using ANN it is essential to train it. Training is a step by step process for calculation of the weight factors and biases. First random initial weights are given to connections. Input data pass layers to generate output data. The resulted data would be compared with real outputs. Changing weight factor may leads to less deviation between inputs and outputs. This process continues until reaching satisfied results. After training process, the network can be used for prediction. To train the neural network, a method must be determined to calculate the error. The degree to which the output from the neural network differs from this predicted output is the error. To train the neural network error should be minimized. To minimize the error, the neuron connection weights and thresholds must be modified. An error function must be defined to calculate the rate of error of the neural network. This error function must be mathematically differentiable. Because the network uses a differentiable activation function, the activations of the output neurons can be thought of as differentiable functions of the input, weights, and thresholds.

There are several ways to find weights that will minimize the error function. The most popular approach is to use the drop descent method. The algorithm that evaluates the derivative of the error function is known as back propagation, because it propagates the errors backward through the network.

3. RESULTS AND DISCUSSION

In this study for calculating pressure drop by the two-fluid model, the momentum balance on each phase (Eq.2, Eq.3) was solved simultaneously.

$$A_w\left(\frac{dp}{dz}\right)-\tau_w S_w \pm \tau_i S_i = 0 \qquad (2)$$

$$A_o\left(\frac{dp}{dz}\right)-\tau_o S_o \pm \tau_i S_i = 0 \qquad (3)$$

where τ_w, τ_o, τ_i are the water, oil and interfacial shear stresses respectively; and S_i, S_w, S_o, are the interfacial length and the wall wetted perimeter of the oil and water phases respectively; A_w and A_o are the cross sectional areas of the water and oil respectively; $\frac{dp}{dz}$ is the pressure drop.

In this research, Al-Wahaibi correlation that was used for the pressure dropis given as

$$\frac{dp}{dz} = 2.4\left(\frac{f_{cor}\rho_m U_m^2}{2D}\right) \qquad (4)$$

where 2.4 is a dimensional coefficient fitting parameter in $\left(\frac{kg}{m^2 s^2}\right)$, ρ_m is the mixture density in $\frac{kg}{m^3}$, U_m is the mixture velocity in $\frac{m}{s}$ and D is the pipe diameter in m. While the corrected friction factor (f_{cor}) will be written as

$$\frac{1}{\sqrt{f_{cor}}} = -2\log\left(\frac{\varepsilon/D}{0.25} - \frac{4.518}{\mathrm{Re}_m}\log\left(\frac{6.9}{\mathrm{Re}_m} + \left(\frac{\varepsilon/D}{0.25}\right)^{1.11}\right)\right) \qquad (5)$$

where ε is the wall roughness, Re_m is the Reynolds number of the oil–water mixture.

In this study, the ANN is used for prediction of pressure drop instead of Al-Wahaibi correlation and two-fluid model. In this work 370 experimental data are studied and pressure drop were predicted according to neural network method and in continue how pressure drop are predicted with this method is explained. The predicted pressure drop versus 370 experimental pressure drops has been presented and compared in Fig. 3.

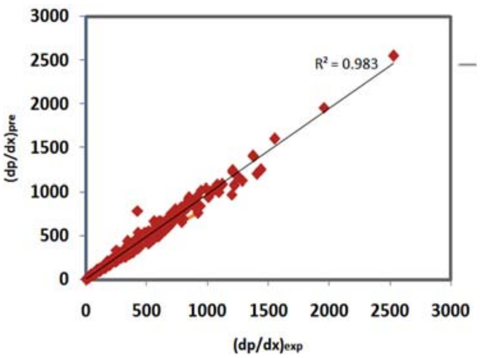

Fig. 3. Accuracy of this study versus experimental data point.

In using neural network, data is divided into two groups including input and output data. Input data is consist of superficial oil velocity, superficial water velocity, ratio of density, ratio of viscosity, diameter of pipe and roughness of the pipe wall while output data is consist of experimental pressure drop.

For improving work accuracy and having less deviation in prediction of experimental data, each run has repeated 5 to 10 times. In all runs of systems, the number of neurons is set on four. In this research, multilayer feed-forward ANN with sigmoidal transfer function with back propagation algorithm was used. A linear transfer function (purelin) was used at the output layer. The training function was “train scaled conjugate gradient back propagation” (trainscg). All calculations were carried out with MATLAB mathematical software with ANN toolbox.
The accuracy of the ANN was validated against the available experimental pressure drop data collected from the literature of separated horizontal oil–water flow for different of condition of flow property and against the two-fluid model and Al-Wahaibi correlation. The accuracy of the predictions was measured by calculating the average absolute percent error (AAPE) of each data source (see Table 2).The average absolute percent error (AAPE) is calculated to evaluate the prediction capability of the correlation.

The absolute errors are considered so the positive errors and the negative errors are not canceled. The equation is expressed as

Table 2 Comparison of the AAPE of pressure drop prediction of the ANN, the two-fluid model and Al-Wahaibi correlation against experimental database obtained from different sources

Source	ANN	Al-Wahaibi correlation	Two-fluid model
Nädler and Mewes (1997)	4.82	10.97	13.94
Angeli and Hewitt (1998)	3.04	6.87	7.74
Angeli and Hewitt (1998)	6.16	16.73	25.02
Rodriguez and Oliemans (2006)	4.42	11.78	29.89
Elseth (2001)	7.12	5.90	9.49
Chakrabarti *et al*. (2005)	7.13	19.46	13.90
Valle and Kvandal (1995)	14.0	2.65	9.30
Al-Wahaibi *et al*. (2007)	8.32	20.78	10. 56
Yiping *et al*. (2005)	6.88	10.66	17.40
Al-Yaari *et al*. (2005)	3.56	10.97	19.73
Yousuf (2011)	4.55	10.31	25.12
All experimental data points	6.36	12.73	15.84

$$AAPE = \left[\frac{1}{n} \sum_{k=1}^{n} \left| \frac{\left(\frac{dp}{dz}\right)_{pre} - \left(\frac{dp}{dz}\right)_{cal}}{\left(\frac{dp}{dz}\right)_{\exp}} \right| \right] \times 100 \quad (6)$$

where subscripts ‘‘pred’’ and ‘‘exp’’ represent the predicted and experimental values, respectively.

As it is obvious from Table 2the AAPE of Al-Wahaibi correlation and two-fluid model are 12.73 and 15.84 while this average for the same systems using neural network is only 6.36. The best agreement was obtained with the data of Angeli and Hewitt (1966), and Al-Yaari *et al*. (1992) at an average absolute error of 3.04 and 3.54 % respectively. The worst agreement was obtained for Valle and Kvandal (2009) data with an average absolute error of 14%, respectively.

The Al-Wahaibi correlation has the best agreement with the data of Valle and Kvandal (2009), and Elseth (2005) at an average absolute error of 2.65 and 5.90% respectively. The worst agreement was obtained for Chakrabarti *et al*. (2006), and Al-Wahaibi *et al*. (2012) data, with an average absolute error of 19.46% and 20.78%, respectively.

The two-fluid model predicted extremely high errors (AAPE are greater than 25%) when compared with data measured by Angeli and Hewitt (1998), Rodriguez and Oliemans (2006), and Yousuf (2011). On the other hand, it gives better presentation when compared to Chakrabarti *et al*. (2005), and Al-Wahaibi *et al*. (2007) data.

4. CONCLUSION

- In this study, the ability of neural networks was examined for their effectiveness to represent a wide array of pressure drop data for separated oil–water flow in horizontal pipes.
- The model proved adept at fitting experimental data set of oil–water separated flow over a wide range of superficial oil velocity, superficial water velocity, viscosity ratio, pipe diameters and pipe materials. So it can be concluded that the application of the ANN models may be considered as an alternative for description of behavior of pressure drop data for oil–water flow.
- The predicted pressure drops agreed reasonably well with the experimental results. The results show that ANN prediction is more accurate than the two-fluid model and Al-Wahaibi correlation. The average absolute percent error using neural network is only 6.36 while this average for Al-Wahaibi correlation and two-fluid model are 12.73 and 15.84

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