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Application of a radial basis function neural network to estimate pressure gradient in water–oil pipelines

Mohamad A. Halali[a], Vahid Azari[a], Milad Arabloo[a,*], Amir H. Mohammadi[b,c], Alireza Bahadori[d,**]

[a] Department of Petroleum Engineering, Petroleum University of Technology, Ahwaz, Iran
[b] MINES ParisTech, CEP/TEP - Centre Énergétique et Procédés, 35 Rue Saint Honoré, 77305 Fontainebleau, France
[c] Thermodynamics Research Unit, School of Engineering, University of KwaZulu-Natal, Howard College Campus, King George V Avenue, Durban 4041, South Africa
[d] School of Environment, Science and Engineering, Southern Cross University, Lismore, NSW, Australia

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ABSTRACT

An accurate determination of the pressure gradient is required for efficient designing of oil and gas wells and pipe systems. Despite the recent improvements in accuracy of models and correlations developed for determining the pressure gradient, they are still incapable of estimating the pressure drop with desired accuracy. Therefore, a robust model is required to determine the pressure gradient precisely. Regarding high performance and great robustness of Artificial Neural Networks for solving science and engineering problems, this paper presents a Radial Basis Function Neural Network (RBF-NN) model to determine the pressure gradient. The model was developed over 994 experimental data sets which are covering a wide range of variables such as oil slip velocity, water slip velocity, pipe diameter, pipe roughness and oil viscosity.

The model estimation indicated an average relative deviation of 0.92%, an average absolute relative deviation of 8.25% and an average correlation factor of 0.99. A comparison between the proposed model and the most prominent models and correlations illustrated that the RBF-NN model exclusively out-performs other models and correlations and the estimated values are in great agreement with the experimental data. At last, a sensitivity analysis was applied to clarify the effect of input parameters in estimated results.

1. Introduction

The flow of two immiscible phases has widespread applications through chemical and petroleum industry. When two fluids with different density get in contact with each other at a horizontal pipe, they often tend to be segregated influenced by gravity force. The heavier phase lies at down and the lighter one flows over it as a separated layer.

Synthesis of water and oil in transportation pipelines has been highlighted for a long distance in petroleum industry as well as other applications of two-phase flow, design of solvent extraction equipment, nuclear reactors film coolers and oil and gas pipelines. Broad range of two-phase flow application in industry along with horizontal oil and gas wells serves as a motivation for a great scrutiny in this domain. Recently, a considerable research effort is being engendered seeking for reliable design methods for multiphase flow [1–5].

More practically, acquaintance with pressure gradient in pipelines is required for an exquisite designation of an energy efficient transportation system such as determining optimum pipe size that can manage the varying flow conditions over the life of a field. Compared to liquid–gas systems, liquid–liquid systems have not been explored to the same range of gas–liquid systems and the theories used in liquid–liquid flows are elaborate developments of models applied for gas–liquid flows [4,6].

The different structure between liquid–gas flow and liquid–liquid flow is fundamentally due to huge momentum transfer capacity and small buoyancy effects in liquid–liquid flows [7]. Liquid–gas system is characterized by a two-fluid system which has a high density and viscosity ratio while the liquid–liquid system consists of two fluids with their density difference relatively low although their viscosity difference can extend over a wider range [4].

As a result, this difference in viscosity ratio causes the dispersion of the droplets of one phase into another, the drag between the two phases and the slip velocities to be considerably different between gas–liquid flows and liquid–liquid flows [7].

Interest to oil–water flows flourished from the 1950's when it was turned out that the addition of water into crude oil could decrease the pressure drop [8–10]. Basically, there are three main approaches

* Corresponding author. Tel: +98-9171405706.
** Corresponding author. Tel: +61266569347; Fax: +61266269857.
E-mail addresses: milad.arabloo@gmail.com (M. Arabloo), Alireza.bahadori@scu.edu.au (A. Bahadori).

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Nomenclature

AARD	average absolute relative deviation
ARD	average relative deviation
ANN	artificial neural network
CFD	computational fluid dynamics
MCNP-X	Monte Carlo *N*-particle extended
MSE	mean squared error
RBF-NN	radial basis function neural network
RMSE	root mean square error
STD	standard deviation errors
TFM	two-fluid model
N	the number of data points

Variables

$\|\|..\|\|$	Euclidean norm
R^2	correlation factor
w_i	weights vector
W	$AJ_2 \times J_3$ weigh matrix
X_i	inputs of the network
f_i	the target output for the *i*th sample in the training set
$f_i(x)$	the *i*th output of the network
σ	parameter that control the smoothness of the interpolating function
$\phi(r)$	nonlinear activation function
$\phi(\cdot)$	Gaussian function
$\phi_0(r)$	constant activation function
Φ	$AJ_2 \times J_3$ matrix

appertain to oil–water flows notions for providing novel models and correlations.

1. Methods with empirical base in nature.
2. Methods which link the correlations to the fact that flow is behaving in a specific flow pattern, either stratified or dispersed.
3. Methods which are based on soft computing analysis.

These three approaches are discussed further below.

2. Calculation of oil–water flow pressure gradient

2.1. Empirical approach

Several empirical correlations were developed in order to find flow pattern and pressure drop in multiphase systems using restricted-range experimental and field data [11–15]. Charles and Lilleleht [16] determined the pressure gradient of liquid–liquid flows regarding to pressure gradient of each phase individually, the proposed model can be representative of pressure drop values of stratified liquid–liquid flows. The model was based on Lockhart and Martinelli [17] model for gas–liquid pipeline flow. Stapelberg and Mewes [18] also made a similar attempt using pipe samples with various diameters. The results tracked the same trend however the effect of changing diameter was noticeably obvious.

Al-Wahaibi [19] developed an empirical correlation pivots on the result of Angeli and Hewitt [6] for estimating the pressure drop over horizontal pipes with oil–water separated flow, the results of his work were validated by experimental values and the absolute average percentage error (AAPE) was 12.74%. These mentioned models are incapable of correlating the pressure drop values in all the regimes of liquid–liquid flow [6].

2.2. Flow pattern based approach

When oil–water two-phase mixture flows through a pipe simultaneously, the two fluids can be distributed in numerous flow configurations and patterns which are highly dependent on fluid physical properties (viscosity, density, and surface tension), operating parameters (phase flow rates) and geometrical parameters (pipe diameter and inclination angle) [5,7]. However these regimes can be categorized in two major flow types: stratified flow where the two fluids are separated and dispersed flow where one phase flows as main and continuous phase and the other phase is dispersed as non-continuous droplets [1,20].

Kurban [21] and Moalem Maron et al. [22] tried the analytical solution of Navier-Stokes equations for full stratified flow field, however this approach is limited to laminar flows and cannot be used in turbulent flows. Furthermore, there have also been attempts to tackle the problem numerically (Charles and Redberger [23], Hall and Hewitt [24] and Kurban [21]). Taitel and Duckler [25], Brauner and Moalem Maron [26] and Valle and Kvandal [27] used Two-fluid model (TFM) for stratified flow on liquid–liquid systems.

Their proposed model is pivoted on the momentum terms for each phase, and the pressure gradient can be obtained from force balance between gravity force along with wall and interface forces [1,6]. Mukherjee et al. [28] and Valle and Utvik [29] investigated dispersed liquid–liquid flow employing homogenous model.

The model is dependent upon mixture velocity, mixture density, mixture friction factor and inner pipe diameter. In this model the two-fluid mixture is recognized as a 'pseudofluid' with fittingly average features which conform to typical terms of single phase flow. Hence, there have to be an effective mixture viscosity which can be attributed to liquid–liquid flow. However, as the viscosity can have anomalous behavior during liquid–liquid flow, the challenging debate about applying this model is calculating effective mixture viscosity [6,30–33].

Angeli and Hewitt [6], Lovick and Angeli [34], Chakrabarti et al. [4], Rodriguez and Oliemans [3] and Al-Wahaibi [19] worked on pressure gradient in a horizontal flow by applying the Two-fluid model in stratified flow and homogenous model for dispersed flow. Angeli and Hewitt [6] put the real pressure drop data in comparison with both the Two-fluid model and the homogenous model and it was observed that none of these two models were capable of estimating the trend of the real data accurately. This poor accordance was attributed to wetting phenomena and drag reduction effects. Indeed, they delved into the effect of tube surface on pressure gradient.

They realized that the reasons of pressure gradient changes are more than just differences in tube roughness in favor of considering the changes in contact angles of the dispersed drops with the tube wall which depend on the type of dispersion and the tube materials, as well as the appearance of drag reduction in the presence of drops in a continuous phase.

Lovick and Angeli [34] had elaborate experimental investigation into the dual continuous flow pattern during horizontal oil–water flow in which the drops of one phase emerged in other phase while the flow was still separated. They successfully generated data on its boundaries, pressure drop, hold-up and phase distribution. They contended that the Two-fluid model was unable to estimate pressure drop and hold-up during dual continuous flow.

Rodriguez and Oliemans [3] generated steady-state data on flow patterns, two-phase pressure drop and holdup over a wide range of flow rates and pipe inclinations. Subsequently, they managed to estimate the pressure drop through horizontal oil–water flow with accuracy of 35% by means of both Two-fluid and Homogenous models.

2.3. Soft computing approach

Nowadays, soft computing approaches are helpful robust tools which play a significant role in analyzing and unraveling challenging pitfalls in various scopes of science and engineering (for instance [35–43]). The preponderance of these computer based approaches includes determining a target function with high degree of accuracy