Prediction of interface level height of stratified liquid-liquid flow using artificial neural network

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Abstract

In this study, artificial neural network (ANN) was used to predict the interface level height (ILH) of two immiscible liquids flowing in a horizontal pipe. A three-layer feed-forward back-propagation (FFBP) neural network was constructed and trained with experimental data of two different liquid-liquid flow systems reported in the literature. The all studied flow patterns were stratified flow (stratified smooth and stratified wavy with or without droplets at interface) . The input parameters of the ANN model were superficial velocity of phases, pipe diameter, the ratio of the lighter phase density to the heavier phase density (ρ_{lp}/ρ_{hp}) and the ratio of the lighter phase viscosity to the heavier phase viscosity (μ_{lp}/μ_{hp}), while the interface level height (ILH) of phases was its output. The Levenberg–Marquardt (LM) algorithm, the hyperbolic tangent sigmoid and the linear activation functions were used for training and developing the ANN. Optimal configuration of the ANN model was determined using minimizing the mean absolute percent error (MAPE) and mean square errors (MSE) between experimental and predicted ILH data by the ANN model. The results showed that the optimal configuration was a network with five neurons in hidden layer that was highly accurate in predicting the interface level. MAPE and correlation coefficient (R) between the experimental and predicted values were determined as 1.8% and 0.9962 for training, and 1.52% and 0.9996 for testing date sets, respectively.

Keywords: Liquid-liquid Flow, Stratified flow, Interface level, Artificial neural network

1. Introduction

Flows of immiscible fluids mixture are very common in the design of a variety of industrial processes and equipment particularly in the petroleum industry, where mixtures of oil and water are often produced and transported together. Depending on the flow conditions, physical properties of the fluids (density and viscosity), the operational variables (flow rate and volume fraction of each phase) and the geometry of the channel (pipe material, diameter and inclination, etc.), the two phases can distribute themselves in several configurations which are called flow regimes or flow patterns. The flow patterns are generally grouped into segregated flow and dispersed flow. In the dispersed flow only one phase is continuous and another phase is dispersed in it in the form of droplets. The stratified and annular flow patterns are usually named separated flows. The stratified flow pattern is characterized by the heavier and lighter phases located at the bottom and top parts of the conduit, respectively. Depending on the liquids velocities, the phases are separated by an interface which can be smooth (stratified smooth), wavy (stratified wavy) or wavy with mixing at the interface (ST & MI). In ST & MI flow, droplets of one phase exist in the layer of another phase and the droplets remain close to the interface.

In the stratified flow pattern, the instantaneous interface level height (ILH) is defined as the height of the interface level of the immiscible fluids from the bottom of the pipe. In the stratified two- or three-phase flow of oil, water and gas mixtures, as the water is the heaviest phase, it flowed at the bottom part of the pipe, so the height of interface level from the pipe bottom is usually called water layer thickness.

Whenever water phase comes into contact with the internal wall of a pipeline, which is known as “water wetting”, there is a potential for an internal corrosion of the pipe inner walls. Corrosion in pipelines can be attributed to the presence of dissolved gases, such as carbon dioxide (CO_2) and hydrogen

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sulphide (H_2S), in water [1]. In such cases, it is necessary to inject the water-soluble corrosion inhibitors into the water phase, and this can be accomplished if the interface level height (water layer thickness) is known. Also, knowing the interface level height, can be useful for a more accurate prediction of the transition from the stratified to non-stratified (dispersed) flows. Hence, it is necessary to be able to accurately predict the interface level height in stratified flows.

Some studies have been conducted to predict the water layer thickness of two- or three-phase stratified flows. Taitel & Dukler [2] proposed a two-fluid model for two-phase stratified gas-liquid flow in pipes. Hall and Hewitt [3] investigated the application of a similar methodology to stratified oil-water flows. Neogi et al. [4] and Taitel et al. [5] suggested a three-layer flow model to estimate the water layer thickness of gas-water-oil three-phase stratified flow. They considered the phases of water and oil and a mixed layer between them as three different "phases" with each phase having its own distinct properties. Also, they assumed all the interfaces between the pure water layer/oil-water mixed layer/pure oil layer as flat. Vedapuri et al. [6] applied this three-layer segregated flow model to estimate the water layer thickness and in situ water phase for oil-water flows. Shi et al. [7] developed a four-layer segregated flow model to calculate in situ water, water film thickness and water film in situ velocity by further dividing the mixed layer into two different layers namely water-in-oil and oil-in-water dispersions. They proposed that these two layers are homogeneous layers and the interfaces are all flat. However their four-layer method gives rise to further difficulties when attempting to determine interfacial shear stresses.

The accurate prediction of interface level is too difficult because of the complex geometry of stratified flow in a pipe [3]. Some investigators suggested the use of artificial neural network (ANN) method to overcome such complex problems. The ANNs can be applied for solving nonlinear, uncertain, or unknown complex engineering problems without a comprehensive understanding of the physical phenomena describing the system under analysis [8]. This method have been successfully used in several problems of gas-liquid flows such as prediction of the flow patterns [9,10], pressure drop [11,12], holdup [13,14] and heat transfer coefficient [15,16]. However, only a few researchers have attempted to model the main parameters of liquid-liquid flows. Shirley et al. [17] trained four different networks for predicting flow pattern of oil–water two-phase in a horizontal pipe based on the flow pattern map reported by Raj et al. [18]. Azizi and Karimi [19] developed an ANN model to predict the pressure gradient in horizontal liquid–liquid separated flow. They used superficial velocities, viscosity ratio and density ratio of oil to water, and roughness and inner diameter of pipe as input parameters of the network. Azizi et al. [20] trained an ANN for prediction of water holdup of oil–water two-phase flow in a pipe with inclination angles of 90°, 75°, 60° and 45° from horizontal.

To the best of the authors' knowledge, there is no study for modelling the interface level height of liquid-liquid stratified flow using ANNs. Hence, in this work the efficiency of ANN techniques to develop a model for the reliable prediction of interface level height of stratified liquid-liquid two-phase flow in horizontal pipes is investigated.

2. The artificial neural network model development

2.1. Basics of artificial neural network

Artificial neural networks (AANs) are inspired by the building and human brain functionality, which can be imagined as a network consisting of densely interconnected processing elements called neurons/nodes. The main advantages of ANNs are learning adaptation, generalization, massive parallelism, robustness, associative storage information and spatiotemporal information processing. The most common network structure utilized in the ANNs is the multilayer perceptron (MLP) or feed-forward with back-propagation (BP) algorithm. This network has an input layer, one or more hidden layers and one output layer. Each layer has a number of artificial neurons, a weight matrix (*w*) and an output vector, and each neuron has a bias (*b*). A layer that produces the network output is called output layer and layers that are between the input and output layers are called hidden layers. Multiple layers of neurons with nonlinear transfer functions permit the network to learn linear and nonlinear relationships between input and output parameters [21]. In the feed-forward networks, individual element inputs are multiplied by weights values and then, the weighted inputs are fed to the summing junction and is summed with the bias of neurons as follows:

$$S=\left(\sum_{i=1}^{P} w_{ji}X_i\right)+b_j \tag{1}$$

in which P is the number of elements of the input vector X_i, and w_{ji} is the interconnection weight between the input and hidden layers, respectively, and S is the sum of the weighted inputs and the bias b [22]. Then, this sum, S, is considered as the input of a transfer/activation function (f) which will make an output. Hyperbolic tangent sigmoid (tansig) in one of the most commonly used transfer functions in the hidden layer(s):

$$f\left(S_j\right)=\frac{e^{S_j}-e^{-S_j}}{e^{S_j}+e^{-S_j}} \tag{2}$$

where $f(S_j)$ is the output of node j, is also an element of the inputs to the neurons of the next layer. Similarly, the hidden layer neurons generates the inputs of all the neurons in the output layer, and then the summation of their weighted inputs and bias of each neuron of output layer passes through a transfer function (commonly linear function), which is the last output, Y_i.

$$Y_i=f\left(\sum_{j=1}^{q} w_{kj}f(S_j)+b_k\right) \tag{3}$$

where q is the number of elements of the hidden layer and w_{kj} is the interconnection weight between the hidden and output layers. In this work, mean square error (MSE) as the performance function between the network outputs and the desired outputs was used as

$$\mathrm{MSE}=\frac{1}{n}\sum_{m=1}^{n}\left(Y_{Exp,m}-Y_{Pred,m}\right)^2 \tag{4}$$

where n is the number of data points, Y_{Pred} is the predicted value obtained from the neural network model and Y_{Exp} is the experimental value. Back-propagation (BP) algorithm adjusts the weights values by allowing the error to spread from output layers towards the lower layers (hidden layer and input layer) for adjusting the weights such that the error decreases at each iteration (epoch). This procedure that is called "training" is iterated again until the output reaches the prescribed tolerance value. During the training process of the MLP network, the values of weights and biases are iteratively adjusted according to the error between the predicted and the target (experimental) values to minimize the network performance function.

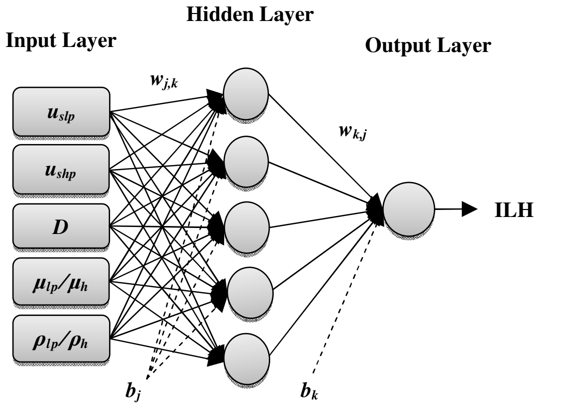
One of the main problems related to the MLP network is over-training or over-fitting, where the produced ANN system can only produce good estimation for known data set while it is unable to give reasonable prediction for new data set [23]. One method to avoid over-training and improve generalization ability of the network is the usage of early-stopping technique [22]. In this method, all data is divided randomly into three subsets: training, validation and testing sets. The training set is applied to train the network (adjusting the weights and the biases values) and the validation set is utilized to ensure the accuracy and the generalization of the developed network during the training process. After increasing the MSE error of the validation set at some consecutive epochs, the training process of the network is terminated, even if further training of the network will continue to minimize the training set error [24]. Once the network training is finished the testing set is employed to examine the final performance of the network.

2.2. The ANN model Development

In this work, MLP network with one hidden layer was applied to predict the interface level height of stratified liquid-liquid flow. The network were designed and trained using experimental data points of Morgan et al. [25] and Ibarra et al. [26] works. Morgan et al. [25] used an aliphatic hydrocarbon oil (Exxsol D80) and an aqueous solution of glycerol (the heavier phase) for studying a set of experiments on liquid–liquid flows in a horizontal circular tube. The obtained results by measuring interface level revealed that for a given superficial mixture velocity, the interface level decreases as the oil input fraction increases. This trend was realized to be more prominent for higher superficial mixture velocities. Also, they observed that the rate of decrease in interface level increases as the superficial mixture velocity is increased. Ibarra et al. [26] investigated the effect of flow velocities and inlet configurations on co-current flows of aliphatic oil (Exxol 140) and water (the heavier phase) in a horizontal pipe. Although they were not reported the measuring results of interface level, in this work those data were used for developing the ANN model. The details of both data sets applied for developing the ANN model are presented in Table 1.

Table 1. Details of the data sets used for developing the ANN model.

	Source	
	Morgan et al. [25]	Ibarra et al. [26]
u_{slp} (m/s)	0.03-0.22	0.05-0.67
u_{shp} (m/s)	0.03-0.25	0.09-0.60
D (cm)	0.26	0.32
ρ_{lp}/ρ_{hp}	0.66	0.83
μ_{lp}/μ_{hp}	0.05	6.00
No. data points	13	20



Superficial velocity of lighter (u_{slp}) and heavier (u_{shp}) phases, pipe diameter (D), the ratio of the lighter phase density to the heavier phase density (ρ_{lp}/ρ_{hp}) and the ratio of the lighter phase viscosity to the heavier phase viscosity (μ_{lp}/μ_{hp}) were chosen as input variables of the network, while the corresponding interface level height (ILH) was selected as output variable. Configuration of the proposed network with 5 neurons in the hidden layer is shown in Fig. 1.

Fig. 1. Structure of the developed single hidden layer ANN model.

In order to validate the trained ANN, the all data were randomly divided into three sets: training (70%), validation (15%) and testing (15%) data sets. All values of inputs and outputs were normalized between –1 and 1. The tansig transfer function was utilized for the hidden layer neurons while the linear transfer function was applied for output layer neuron. There are several BP learning algorithm. In this study, Levenberg-Marquardt (LM) algorithm was preferred owing to providing fast convergence and stability in training of ANN. The number of neurons in the input and output layers is equal to the number of input and output variables, respectively, whereas the optimum number of neurons in the hidden layer depends on the complexity of the problem. The topology of an MLP network associated with the number of neurons in the hidden layer exerts a substantial influence on prediction accuracy and generalization ability of the network and consequently should be optimized. However, there is no a general rule for the determination of the optimal topology of MLP network and it is commonly concluded through the trial-and-error method [27].

3. Results and discussion

In this study, different single hidden layer networks were formulated and applied to predict the ILH. The number of neurons in each hidden layer were varied from 1 to 20 so that each network was repeatedly run for 100 times. The accuracy of the networks was evaluated by MSE, mean absolute percent error (MAPE) and correlation coefficient (R) between the experimental and predicted values:

$$\mathrm{MAPE} = \left[\frac{1}{n} \sum_{m=1}^{n} \left| \frac{Y_{Exp,m} - Y_{Pred,m}}{Y_{Exp,m}} \right| \right] \times 100 \qquad (5)$$

$$R = \left(\frac{\sum_{m=1}^{n} (Y_{Pred,m} - \overline{Y}_{Pred})(Y_{Exp,m} - \overline{Y}_{Exp})}{\sqrt{\sum_{m=1}^{n} (Y_{Pred,m} - \overline{Y}_{Pred})^2 \sum_{m=1}^{n} (Y_{Exp,m} - \overline{Y}_{Exp})^2}} \right) \quad (6)$$

where $\overline{Y}_{Exp}$ and $\overline{Y}_{Pred}$ are the average of the experimental and predicted values, respectively. The best obtained results for different numbers of neurons in the single hidden layer networks for testing data are shown in Fig. 2.

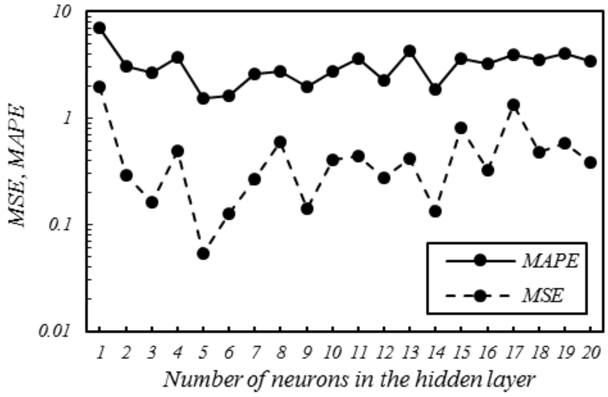


Fig. 2. Variations of minimum MSE and MAPE of testing data against the different numbers of neurons in hidden layer

As is shown in this figure, the network with 5 neurons in the hidden layer (5-5-1) was found to be the optimum network with the best performance in which the MSE and the MAPE of testing data were achieved 0.05429 and 1.52%, respectively. In Fig. 3, MSE against epochs during the training process of the optimum network (5-5-1) are plotted, in which the best results were achieved in epoch of 8 with minimum MSE of 0.51038 for validation data set.

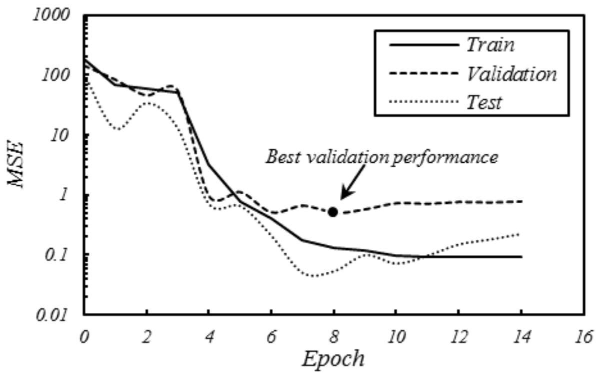


Fig. 3. Variations of mean squared error (MSE) versus epoch during the training of the optimal network.

Fig. 4 shows the scatter plot of the predicted ILH values by the developed ANN model against experimental values for the all data sets. Also, Table 2 represent the details of performance of the ANN for all data sets.

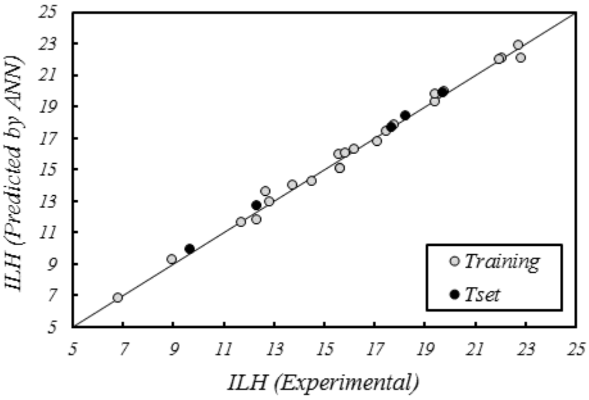


Fig. 4. Scatter plot of the predicted ILH by the ANN model versus the experimental data for training and testing data sets.

Table 2. Performance evaluation of the developed ANN model for training, validation, testing and all data sets.

Data set	MSE	MAPE (%)	R
Training	0.13194	1.80	0.9962
Validation	0.51038	3.34	0.9864
Test	0.05429	1.52	0.9996
All data	0.17751	1.99	0.9951

As can be seen from Table 2, the accuracy between the neural network predictions and experimental data was attained with low mean absolute percent error and high correlation coefficient for both training data set (MAPE = 1.8%, R = 0.9962) and testing data set (MAPE = 1.52% and R = 0.9996). The MAPE and R value for all data were also calculated as 1.98% and 0.99951, respectively. These results show the excellent fitting between the experimental and the predicted ILH, and so confirm the high ability of the developed ANN to predict the interface level height of the stratified liquid-liquid flow.

4. Conclusion

In this work a three-layer feed-forward back propagation (FFBP) neural network model with 5 neurons in the hidden layer as optimal configuration were utilized to predict the interface level height of stratified liquid-liquid flow. The network was designed and trained using the experimental data points of Morgan et al. [25] and Ibarra et al. [26] works. Input variables of this network included superficial velocity of phases, pipe diameter, the ratio of the lighter phase density to the heavier phase density (ρ_{lp}/ρ_{hp}) and the ratio of the lighter phase viscosity to the heavier phase viscosity (μ_{lp}/μ_{hp}), while the interface level height (ILH) of phases was selected as its output variable. The obtained results from the optimal structure of network confirmed that the proposed ANN model have a high accuracy for predicting the ILH under all studied situations with a MAPE of 1.8% and R value of 0.9962 for training data and MAPE of 1.52% and R value of 0.9996 for tasting data. As a result, the ANNs can be used for predicting the interface level height of stratified liquid-liquid flow or the water thickness layer of stratified oil-water flow with a high accuracy. Although in this study a relatively small number of data was used to train the network, but the network was able to accurately predict the testing data set. For future work, by training the network using data obtained from more sources with various flow conditions, a more comprehensive model can be achieved.

References

[1] Cai, J., Li, C., Tang, X., Ayello, F., Richter, S., and Nesic, S., Experimental study of water wetting in oil–water two phase flow—Horizontal flow of model oil, *Chemical Engineering Science,* 73, pp. 334-344, 2012.

[2] Taitel, Y., and Dukler, A. E., A model for predicting flow regime transitions in horizontal and near horizontal gas-liquid flow, *AIChE Journal,* 22, pp. 47-55, 1976.

[3] Hall, A. R., and Hewitt, G. F., Application of two-fluid analysis to laminar stratified oil–water flows, *International Journal of Multiphase Flow,* 19, pp. 711-717, 1993.

[4] Neogi, S., Lee, A. H. and Jepson, W. P., A model for multiphase (gas-water-oil) stratified flow in horizontal pipelines, *SPE Asia Pacific Oil and Gas Conference,* SPE 28799, pp. 553-561, Melbourne, Australia, 7-10 November, 1994.

[5] Taitel, Y., Barnea, D. and Brill, J. P., Stratified three-phase flow in pipes, *International Journal of Multiphase Flow,* 21, pp. 53-60, 1995.

[6] Vedapuri, D., Bessette, D., and Jepson, W. P., A segregated flow model to predict water layer thickness in oil-water flows in horizontal and slightly inclined pipelines, *8th International Conference on Multiphase'97,* pp. 75-105, Cannes, France, 18-20 June 1997.

[7] Shi, H., Wang, H., and Jepson, W. P., Prediction of water film thickness and velocity for corrosion rate calculation in oil-water flows, *Corrosion 2002,* Paper No. 02500, pp. 1-18, Denver, Colorado, 7-11 April, 2002.

[8] Cong, T., Su, G., Qiu, S., and Tian, W., Applications of ANNs in flow and heat transfer problems in nuclear engineering: A review work, *Progress in Nuclear Energy,* 62, pp. 54-71, 2013.

[9] Sharma, H., Das, G., and Samanta, A. N., ANN–based prediction of two-phase gas–liquid flow patterns in a circular conduit, *AIChE Journal,* 52, pp. 3018-3028, 2006.

[10] Tambouratzis, T., and Pazsit, I., A general regression artificial neural network for two-phase flow regime identification, *Annals of Nuclear Energy,* 37, pp. 672-680, 2010.

[11] Osman, E. S. A., and Aggour, M. A., Artificial neural network model for accurate prediction of pressure drop in horizontal and near-horizontal-multiphase flow, *Petroleum Science and Technology,* 20, pp. 1-15, 2002.

[12] Alizadehdakhel, A., Rahimi, M., Sanjari, J., and Alsairafi, A. A., CFD and artificial neural network modeling of two-phase flow pressure drop, *International Communications in Heat and Mass Transfer,* 36, pp. 850-856, 2009.

[13] Shippen, M. E., and Scott, S. L., A neural network model for prediction of liquid holdup in two-phase horizontal flow, *Proceedings of the SPE Annual Technical Conference and Exhibition,* San Antonio, Texas, Paper SPE-77499, 29 September-2 October, 2002.

[14] Castillo, A. Á. D., Santoyo, E., and Garcia-Valladare, O., A new void fraction correlation inferred from artificial neural networks for modeling two-phase flows in geothermal wells, *Computers & Geosciences,* 41, pp. 25-39, 2012.

[15] Sobhanifar, N., Ahmadloo, E., and Azizi, S., Prediction of two-phase heat transfer coefficients in a horizontal pipe for different inclined positions with artificial neural networks. *ASME Journal of Heat Transfer,* 137, Article No. (061009), 2015.

[16] Ghajar, A. J., Tam, L. M., and Tam, S. C., Improved heat transfer correlation in the transition region for a circular tube with three inlet configurations using artificial neural networks, *Heat Transfer Engineering,* 25, pp. 30-40, 2004.

[17] Shirley, R., Chakrabarti, D. P., and Das, G., Artificial neural networks in liquid–liquid two-phase flow, *Chemical Engineering Communications,* 199, pp. 1520-1542, 2012.

[18] Raj, T. S., Chakrabarti, D. P., and Das, G., Liquid–liquid stratified flow through horizontal conduit, *Chemical Engineering & Technology,* 28, pp. 899-907, 2005.

[19] Azizi, S., and Karimi, H., An artificial neural network model for predicting the pressure gradient in horizontal oil–water separated flow, *Journal of Chemical and Petroleum Engineering,* 49, pp. 131-141, 2015.

[20] Azizi, S., Awad, M. M., and Ahmadloo, E., Prediction of water holdup in vertical and inclined oil-water two-phase flow using artificial neural network, *International Journal of Multiphase Flow,* 80, pp. 181-187, 2016.

[21] Mohanraj, M., Jayaraj, S., and Muraleedharan, C., Applications of artificial neural networks for refrigeration, air–conditioning and heat pump systems—A review. *Renewable and Sustainable Energy Reviews,* 16, pp. 150-172, 2012.

[22] Haykin, S., *Neural Networks: A Comprehensive Foundation,* First ed., Mc Millan, NJ, New York, 1994.

[23] Sayyad, H., Manshad, A. K., and Rostami, H., Application of hybrid neural particle swarm optimization algorithm for prediction of MMP, *Fuel,* 116, pp. 625-633, 2014.

[24] Jung, S., and Kwon, S., Weighted error functions in artificial neural networks for improved wind energy potential estimation, *Applied Energy,* 111, pp. 778-790, 2013.

[25] Morgan, R. G., Markides, C. N., Zadrazil, I., and Hewitt, G. F., Characteristics of horizontal liquid–liquid flows in a circular pipe using simultaneous high-speed laser-induced fluorescence and particle velocimetry, *International Journal of Multiphase Flow,* 49, pp. 99-118, 2013.

[26] Ibarra, R ., Matar, O. K., Markides, C. N., and Zadrazil, I., An experimental study of oil-water flows in horizontal pipes, *17th International Conference on Multiphase Technology,* Cannes, France, pp. 169-183, 10-12 June 2015.

[27] Terrence, L. F., *Feedforward neural network methodology,* First ed., Springer, New York, 1999.