International Conference on Applied Energy 2019
Aug 12-15, 2019, Västerås, Sweden
Paper ID: 0626

IDENTIFICATION OF FLOW PATTERNS IN UPWARD INCLINED TWO-PHASE FLOWS BY ARTIFICIAL NEURAL NETWORK

Zi Lin[1], Xiaolei Liu[2*]

1 Department of Naval Architecture, Ocean and Marine Engineering, University of Strathclyde, Glasgow, G4 0LZ, United Kingdom

2 School of Engineering, University of Glasgow, Glasgow, G12 8QQ, United Kingdom

ABSTRACT

This paper presented a methodology of artificial neural network (ANN) for the prediction of flow patterns in two-phase air-water flow along upward inclined pipes. In the built ANN model, superficial velocity of air, superficial velocity of water, and inclined angle were set as inputs while the quantified flow patterns were defined as the output. In total, 1952 experimental data points that were reported in the literature were trained and tested by the designed network structure. The predicting accuracies of stratified smooth, stratified wavy, annular, intermittent, bubble flow are all above 90%, with the exception of dispersed bubble flow.

Keywords: artificial neural network (ANN); two-phase flow; flow patterns.

1. INTRODUCTION

Two-phase flow is commonly significant for various energy sectors, such as petroleum and nuclear industries. It also plays an essential role in subsea operations, such as fluid transportations in pipelines. Accurate predictions of two-phase characteristics are highly desired by industries, including flow pattern forecasting. Numbers of previous studies have experimentally investigated flow patterns in the vertical, horizon, and inclined pipes [1],[2],[3].

The term of flow patterns is used to describe the spatial distribution of phases, occurring during multiphase flow in a pipe. Prediction of flow patterns is one of the fundamental issues in two-phase flow studies, which can be used to support the industry for a better design in their commercial flow loops.

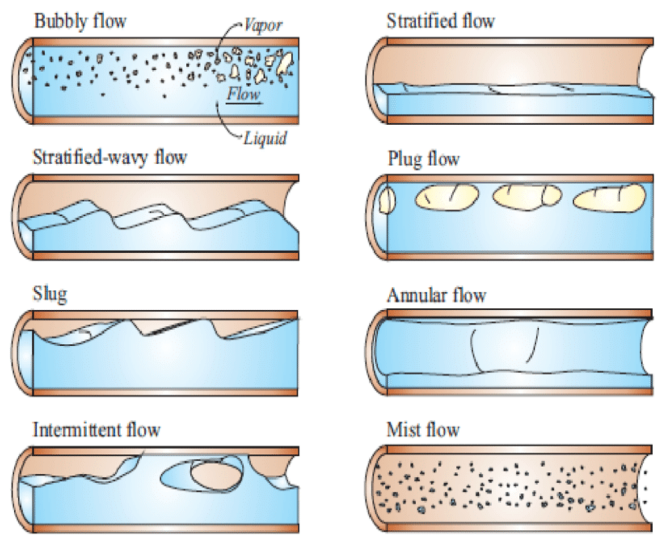

Fig 1 Flow patterns [7].

The commonly accepted horizontal flow patterns are summarized in **Fig. 1**, which are classified in mist, stratified, stratified wavy, annular, intermittent, slug, plug, and bubble flow. For two-phase vertical flows, one of the most widely accepted flow regime classifications was suggested by Hewitt and Hall-Taylor [4], who defined basic flow patterns as bubble, slug, churn, and annular in upward vertical two-phase flows.

Comparing to vertical and horizontal flow investigations, fewer research have been carried out on upward or downward inclined two-phase flows. In this paper, a fully connected ANN model was designed for flow pattern identification with consideration of upwards inclination angles.

2. EXPERIMENTAL DATASET

The used data was extracted from the database built by Pereyra et al. (2012) [5], which was originally used to quantify the confidence level of methods in air-water two-phase flow pattern prediction. The experimental setup consists of a pipe with the diameter of 50.8 mm. The inclined angles varied from 0° to 90°. The air superficial velocity varied from 0.016 to 40 m/s while the water superficial velocity changed in the range of 0.0022 ~ 6.3 m/s.

3. ARTIFICIAL NEURAL NETWORK MODEL

Artificial neural network (ANN) is a biologically inspired system, which consists of interconnected neurons in input and output layers, linking through defined weights and biases [6]. In this paper, TensorFlow, which is developed by Google, was used to perform a fully connected artificial neural network model. It is an end-to-end open source platform for machine learning, with a focus on deep learning. The model itself has three layers and has been trained for 15000 epochs. **Fig 2** shows the schematic of the designed ANN.

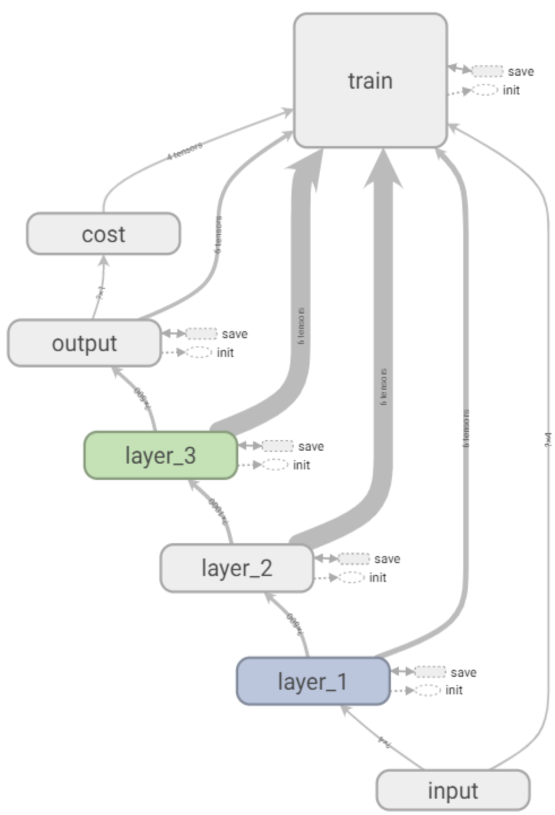

Fig 2 Defined ANN configuration.

The Min-Max scaler, which is one of the most frequently used scaling algorithms is applied in the model to shrink the range of training and testing data into the range between 0 and 1. The corresponding formula can be expressed as:

$$X_{std} = \frac{x_i - \min(x)}{\max(x) - \min(x)} \tag{1}$$

$$X_{scaled} = X_{std} \tag{2}$$

where x_i is the original value; X_{std} is the normalized value; $\min(x)$and $\max(x)$ are the minimum and the maximum value in the span, respectively; X_{scaled} is the scaled value.

The learning rate is set as 0.0001 while the training/testing epochs is defined as 15000. The initialization of network weights was realized through the Xavier initialization to make sure the weights are located in a reasonable range. The activation function, also known as the transfer function, was applied to get the outputs of nodes. More specifically, the ReLU (Rectified Linear Unit) non-linear activation functions were applied in this study. The function of *tf.matmul* is used to create matrixes that contain multiple tensors. The following correlations are used to implement the fully connected layers:

$$H_i = \sum_{j=1}^{m} x_i w_{ij} + b_j \tag{3}$$

$$h = ReLU(H_i) \tag{4}$$

where H_i is the net input of neuron j in output or deeper hidden layer; x_i is the input of neuron j; w_{ij} is the weights that linked neuron i and neuron j; b_j is the bias associated with neuron j.

The designed ANN was trained with 1952 groups of data that were recorded by a pipe with a diameter of 2 inch, where superficial velocity of air, superficial velocity of water, and inclined angle were set as input variables. The outputs are defined through quantified flow patterns, representing 1 - Dispersed Bubble, 2 - Stratified Smooth, 3 - Stratified Wavy, 4 - Annular, 5 - Intermittent, and 6 - Bubble. Most numbers of tests were conducted in the superficial velocity interval of 0.01 ~ 10 m/s for both liquid and gas phases while variations of upward inclination angles were relatively evenly distributed in the range of 0 ~ 90°.

Our model includes three fully connected hidden layers and output layer. For every 100 epochs, the mean accuracy is calculated. The loss function of Mean Square Error (MSR) is used to resolve how far the predicted values deviate from the actual values in the testing data, which can be expressed as:

$$MSR = \frac{1}{n}\sum_{i=1}^{n}\left[\frac{(M_{predicted})_i - (M_{actual})_i}{(M_{actual})_i}\right]^2 \tag{5}$$

where n is the number of tests; $M_{predicted}$ is the predicted value from the ANN model; $M_{experimental}$ is the recorded value in the experiments.

4. RESULTS AND DISCUSSIONS

As presented in **Fig 3**, the network model started to converge after 12000 training/testing iterations while MSE = 0.01 for the testing data.

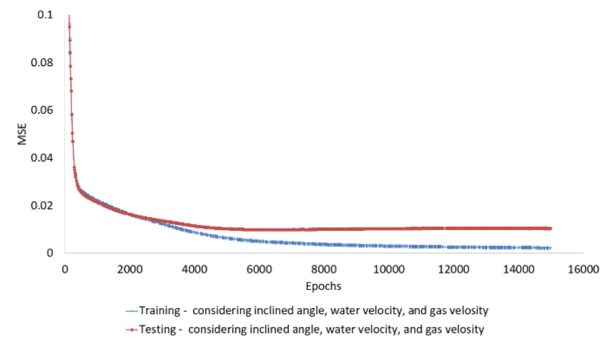

Fig 3 Variations of mean squared error (MSE) over 15000 iterations of the ANN training and testing loops.

The predicted flow patterns by the neural network are compared with the experimental results in **Fig 4**. The predicted results are satisfactory for most data points under all inclinations. Along the Y axis, the numeric flow patterns are: 1 - Dispersed Bubble, 2 - Stratified Smooth, 3 - Stratified Wavy, 4 - Annular, 5 - Intermittent, and 6 - Bubble. The classification accuracies in flow pattern predictions of stratified smooth, stratified wavy, annular, intermittent, bubble flow are all above 90%, with the exception of dispersed bubble flow.

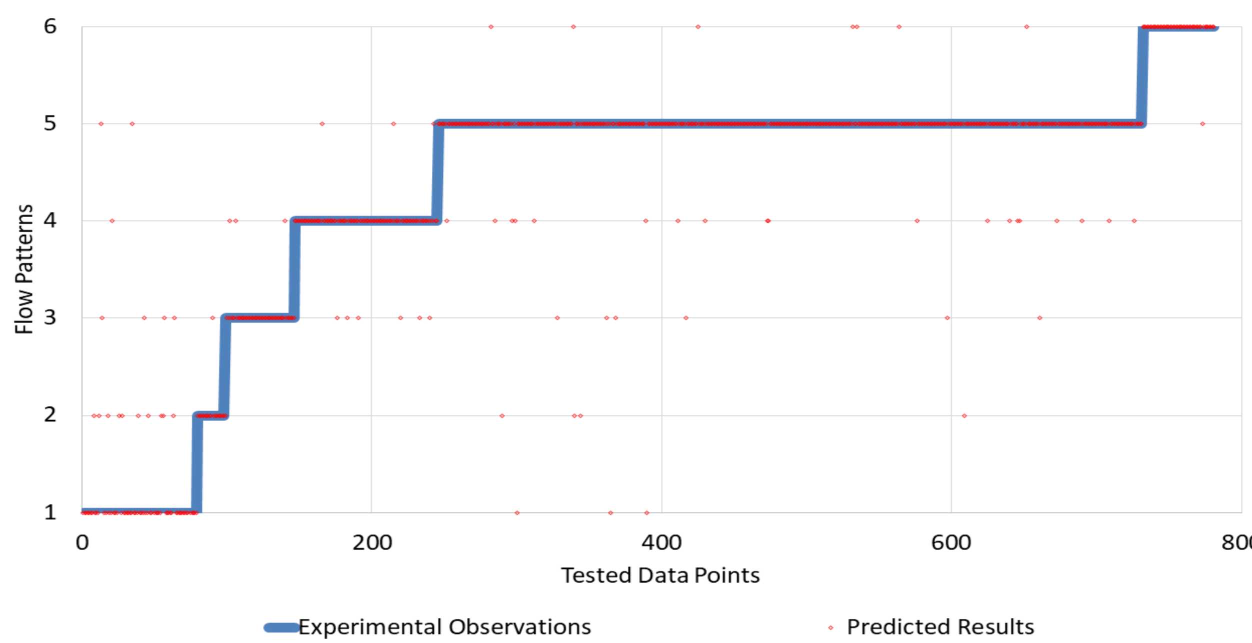

Fig 4 Comparisons of experimental and predicted flow patterns during air-water two-phase flow in a 2-inch pipe at atmospheric conditions and different inclined angles.

In order to further validate the reliability of the built ANN model, it was further validated with Barnea correlations [1]. The dataset consists of superficial velocity of air (0.03 ~ 40 m/s), superficial velocity of

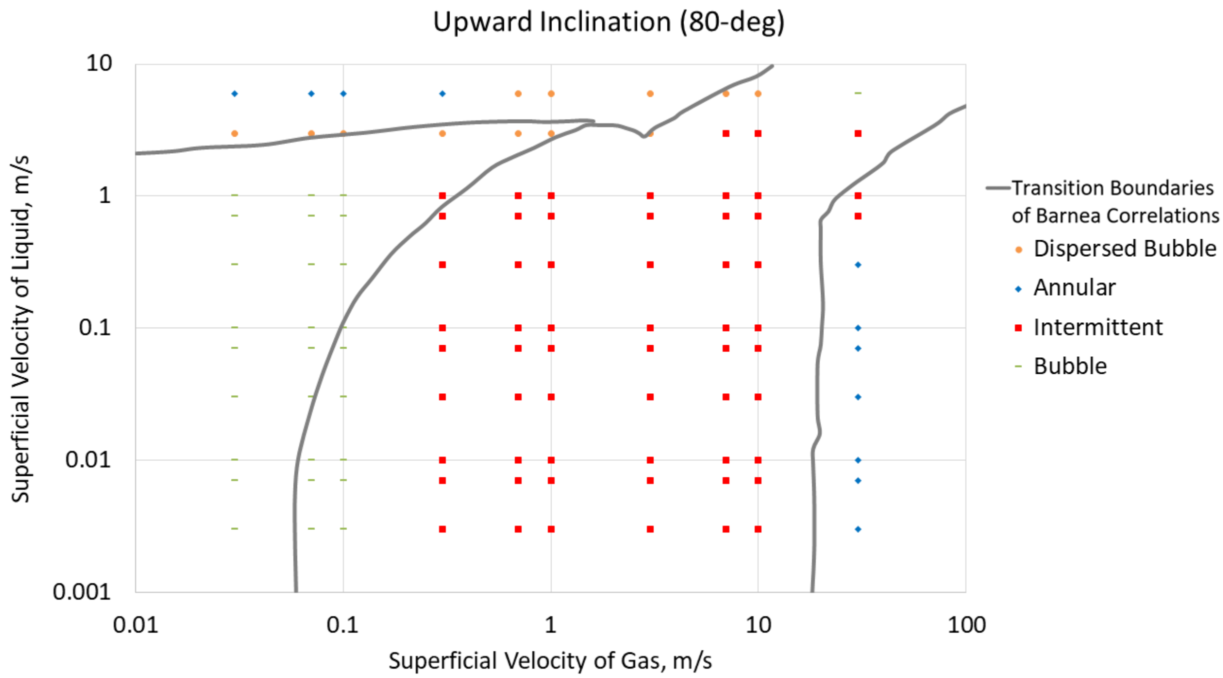

Fig 5 Comparison of flow pattern predictions between ANN model (dotted points) and Barnea correlations (full lines) during air-water two-phase flow in a 2-inch, upward inclined (80°) pipe at atmospheric conditions.

water (0.003 ~ 6 m/s), and inclination angles (0°, 1°, 30°, 80°, and 90°).

The comparing results of flow pattern predictions between ANN model (dotted points) and Barnea correlations (full lines) during air-water two-phase flow in a 2-inch with an upward inclined angle of 80° is presented in **Fig.5**. The ANN model performed well for Stratified Smooth, Stratified Wavy, Annular, Intermittent, and Bubble flow. However, the ANN model has difficulties in recognizing dispersed bubble flow. More specifically, in **Fig 5**, certain dispersed bubble flow points have been identified as annular or intermittent flow.

5. CONCLUSIONS

In this paper, a fully connected neural network was established to predict flow patterns under different inclinations. The inclined angles of experimental setup varied from 0° to 90°. In this model, superficial velocities of air & water as wells as inclined angles were defined as input variables for predicting flow patterns. The ANN has been trained and tested for 15000 epochs. The obtained model provided an accepted MSE = 0.01 for over 700 testing data points. In addition, the designed ANN model was further validated by the Barnea correlations. Due to the capacity of this model, it is expected that this ANN can be used to predict flow patterns in a 1-inch inclined pipe.

REFERENCE

[1] D. Barnea, “A unified model for predicting transitions for the whole pipe inclinations,” *Int. J. Multiph. Flow*, vol. 13, no. I, pp. 1–12, 1987.

[2] C. Mata, E. Pereyra, J. L. Trallero, and D. D. Joseph, “Stability of stratified gas – liquid flows,” *Int. J. Multiph. Flow*, vol. 28, pp. 1249–1268, 2002.

[3] N. K. Omebere-Iyari, B. J. Azzopardi, and Y. Ladam, “Two-Phase Flow Patterns in Large Diameter Vertical Pipes at High Pressures,” *Fluid Mech. Transp. Phenom.*, vol. 53, no. 10, 2007.

[4] G.F. HEWITT and N.S. HALL-TAYLOR, *Annular Two-Phase Flow*. Elsevier Ltd, 1970.

[5] E. Pereyra, C. Torres, R. Mohan, L. Gomez, G. Kouba, and O. Shoham, “A methodology and database to quantify the confidence level of methods for gas – liquid two-phase flow pattern prediction,” *Chem. Eng. Res. Des.*, vol. 90, no. 4, pp. 507–513, 2011.

[6] S. A. Razzak, S. M. Rahman, M. M. Hossain, and J. Zhu, “Investigation of artificial neural network methodology for modeling of a liquid-solid circulating fluidized bed riser,” *Powder Technol.*, vol. 229, pp. 71–77, 2012.

[7] J. R Thome and A. Cioncolini, “Two-Phase Flow Pattern Maps for Macrochannels,” 2015, pp. 5–45.