Proceedings of the 2nd International Conference on Fluid Flow, Heat and Mass Transfer
Ottawa, Ontario, Canada, April 30 – May 1, 2015
Paper No. 133

Two-Phase Flow Regimes Identification using Artificial Neural Network with Nonlinear Normalization

Mustafa Al-Naser, Moustafa Elshafei
King Fahd University of Petroleum & Minerals, System Engineering Department
Dhahran, East, Saudi Arabia
g200086290@kfupm.edu.sa; elshafei@kfupm.edu.sa

Abdelsalam Al-Sarkhi
King Fahd University of Petroleum & Minerals, Mechanical Engineering Department
Dhahran, East, Saudi Arabia
alsarkhi@kfupm.edu.sa

Abstract- Multiphase flow measurement is a very challenging issue in process industry. There are several techniques to estimate multiphase flow parameters. However, these techniques need correct identification of the flow regimes first. Artificial Intelligence is one promising technique for identification of the flow regimes. In this paper we used Artificial Neural Network in identifying the flow regimes using multiphase flow parameters such as superficial velocity of liquid and gas, pressure drop, liquid hold up and Reynolds' number. We proposed a pre-processing stage to normalize large data range and to reduce overlapping between flow regimes. It was shown that using the natural logarithms of certain flow parameters as inputs to neural network improved the identification process.

Keywords: Flow Regimes, Artificial Intelligence, Natural Logarithmic Normalization.

1. Introduction

Multiphase flow refers to the simultaneous flow of two phases or more and they can be liquid, gas, solid, two components from the same phase such oil and water, or two phases single component such as water vapor and liquid. Multiphase flow is encountered in many industries and processes such as oil and gas industry and petrochemical process, and there is an increasing demand for more accurate multiphase metering. Several approaches were reported in the literature to estimate the flow rate of each phase in multi-phase flow. One of the common difficulties in these techniques is the need to identify the flow regime first for better estimation of the multiphase flow parameters. Flow regimes are more than 20 types including bubble flow, slug flow, annular flow and many more. These flow regimes depend on many factors such as pipe inclination, phase composition and physical properties, and velocity of the individual fluids. The overlapping between these flow regimes especially at the transient zones make accurate identification more difficult to achieve. The flow regime identification errors, in turn, introduce metering errors, as conventional meters usually assume one type of flow regimes and are tuned based on it. Accordingly, correct identification of the flow regimes could greatly improve the multiphase flow measurement (Bratland O. (2008)).

Artificial Intelligence is a promising technique to identify flow regimes. Xiea et al. (2004) used transportable artificial neural network for the classification of flow regimes. They studied three phase flow (Gas/Liquid/Fiber) in Vertical Pipe. They used 7 inputs in terms of normalized pressure signals (standard deviation, coefficients of skewness and kurtosis, and several second-order correlation terms). They reported classification problems in the transition zone. Rosa et al (2010) tried to develop an expert system to identify the flow regime using clustering techniques and studied 6 flow patterns. Four statistical momentums (mean, standard deviation, skewness and kurtosis) and Probability Density Function (PDF) of instantaneous line average void fraction are used as inputs to the system. They used clustering data clustering methods. They showed that clustering algorithms have low correct identification rate because of confusion at transition zones when number of flow regimes is large. They concluded that Knowledge base is required to assist neural network

El-Sebakhy (2010) used adaptive Neuro Fuzzy Interference System (ANFIS) for flow regimes classifications. He selected ANFIS because of its ability to predict the output in uncertain conditions. ANN Inputs are liquid superficial velocity, gas superficial velocity, pressure, temperature, fluid properties. He studied 4 flow regimes: Annular, Slug, Wavy and stratified. His results showed high correct classification rate, but suffered from misclassifications at transition zones. Murat and Ertan (2012) implemented three AI techniques: Nearest Neighborhood (NN), Back propagation Neural Network (BNN) and classification tree (CT) to identify the flow regime and estimate liquid hold up. He used Reynolds number for both gas and liquid as neural network inputs. He considered 7 flow regimes in his study. To improve the performance, he scaled the gas Reynolds number to overcome the issue of overlapping between flow regimes. He concluded that BNN has best performance in flow regimes identification.

In this work we used simple ANN with only two inputs to identify 4 types of multiphase flow regimes. We studied pre-processing the data before feeding them to the neural network by using nonlinear transformation of the original parameters. This pre-processing stage helps in scaling large data range properly to reduce the effect of overlapping between flow regimes, and achieves better identification of the flow type in the transition regions.

First, the simulation method of multiphase flow using the unified model of Zhang et al. (2003) and Zanng and Sarica (2006) is discussed in Section 2. The selected Multiphase flow regimes and the input parameters are explained briefly in section 3. Finally, the simulation for various ANN inputs sets, and the analysis and discussion, are presented in Section 4.

2. Unified Model

The unified model is used for generating data for testing various flow classification techniques. Zhang et al., (2003), and Zhang and Sarica (2006) proposed a unified model for prediction of gas-oil-water flow behavior in wellbores and pipelines based on slug dynamics. This model describes three-phase flow based on two criteria: gas-liquid flow pattern and oil-water mixing status. The three-phase flow was treated as gas-liquid two-phase flow if the two liquids are fully mixed or as a three-layer stratified flow at low flow rates in horizontal or slightly inclined pipes. Closure relationships describing the distribution between the two liquid phases were proposed. Experimental data for gas-oil-water pipe flow from many studies in literature were used to evaluate the model. The Zhang et al. (2003) flow pattern map in their unified model was used to compare also with Taitel and Dukler (1976) flow pattern maps for the gas-liquid flow patterns and showed excellent agreement. Due to the confidence received by unified model in literature, it was decided to use the resulted data from the Unified model to train our ANN in this study.

3. Flow Regimes Maps

There are many flow pattern maps to describe flow regimes using different multiphase flow parameters. Superficial velocities of liquid and gas are popular parameters on the two-dimensional axis’s of the map for identification of flow regimes as shown in Fig. 1.

Annular flow is characterized by the presence of a liquid film flowing on the channel wall in an annulus-shaped flow, the gas flows in the gas core. Annular flow happens at high gas superficial velocities.

In stratified flow the two phases are separated from each other by a continuous interface. For example, water flows at the bottom of a horizontal pipe. The interface may be smooth or wavy according to the gas flow rate.

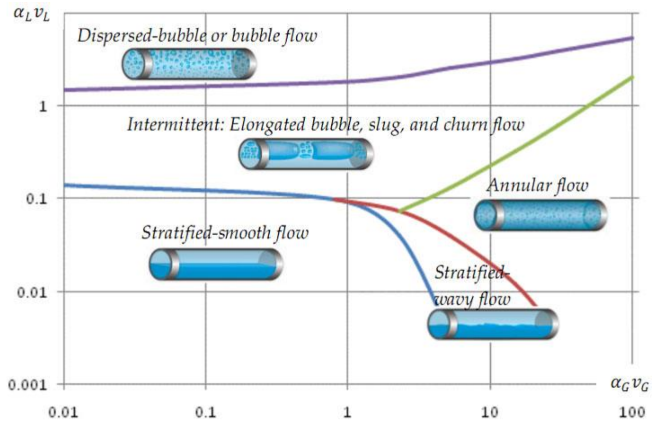

Fig. 1. Gas-liquid flow pattern map in a horizontal. (Bratland O. (2009))

Dispersed bubble flow is characterized by the flow where one phase is dispersed in the other continuous phase. For example, in gas-liquid flow the gas phase becomes bubble flow when the gas flow rate is small compared to the liquid flow rate. In Intermittent flow, liquid and gas can alternate in flow causing sequences of plug/slug patterns.

In Fig.1 α_L is the volume fraction of the liquid phase, and α_G is the volume fraction of the gas phase.

The superficial velocity of liquid (V_{sL}) and gas (V_{sG}) can be defined as:

$$V_{sL} = \frac{q_L}{A} = \alpha_L v_L \tag{1}$$

$$V_{sG} = \frac{q_G}{A} = \alpha_G v_G \tag{2}$$

Where: q_L and q_G are volume flow rates of the liquid and gas respectively.

Liquid Hold H_L is another important multiphase flow parameter, which can be defined as:

$$H_L = \frac{A_L}{A} \tag{3}$$

Where: A is pipe cross sectional area and A_L is the cross sectional area occupied by liquid.

Another multiphase flow parameter is Pressure Drop per unit pipe length $\frac{dP}{dx}$ which can be calculated as:

$$\frac{dP}{dx} = \frac{dP}{dx}_{acc} + \frac{dP}{dx}_f + \frac{dP}{dx}_g \tag{4}$$

Where:

$\frac{dP}{dx}_{acc}$ is the acceleration pressure gradient.

$\frac{dP}{dx}_f$ is the frictional pressure gradient.

$\frac{dP}{dx}_g$ is the gravitational pressure gradient.

However, these maps depends on dimensional parameters which means they work for a certain pipe diameters and flow conditions. Reynolds number for liquid (Re_L) and gas (Re_G) are candidate parameters that can be used to develop a dimensionless maps:

$$Re_L = \frac{\rho_L V_{SL} D}{\mu_L} \tag{5}$$

$$Re_G = \frac{\rho_G V_{SG} D}{\mu_G} \tag{6}$$

Where:
ρ_L, ρ_G are densities of liquid and gas respectively.
μ_L, μ_G are viscosities of liquid and gas respectively.
D is the pipe diameter.

4. Simulation

In this work we considered two-phase flow in four flow regimes: Stratified (STR), Dispersed Bubbles (DB), Intermittent (INT), and Annular (AN). We studied a horizontal pipe with diameters of 2.54 cm, and used 946 points divided as follows: 277 for Annular, 264 for Dispersed Bubble, 252 Intermittent and 153 for Stratified. The Data is divided into 70% for Training, 15 % for Validation and 15 % for Testing. In each case, the Neural Network model has 2 inputs, one hidden layer with 20 neurons, and 4 outputs. We considered the following pairs of multiphase parameters; (V_{sG}, V_{sL}), Total pressure drop and liquid hold (dP, HL), and the Reynolds numbers for the liquid and gas flows (Re_L, Re_G) Since Neural Network cannot handle nonnumeric outputs, we represent the flow regimes with the target numeric values shown in Table.1.

Table 1. Numerical representation of flow regimes.

Flow Regime	Numerical Value
Annular	1000
Dispersed Bubble	0100
Intermittent	0010
Stratified	0001

Different configurations of input parameters are used in neural networks model:

1. Liquid Superficial velocity (V_{sL}) and Gas Superficial velocity (V_{sG}).
2. Natural Logarithmic of V_{sL} and V_{sG}
3. Total Pressure Drop (dP) and Liquid Hold up (HL).
4. Natural Logarithmic of dP and HL.
5. Liquid Reynolds Number (Re_L) and Gas Reynolds Number (Re_G).
6. Natural Logarithmic of Re_L, Re_G.

Fig. 2 indicates some regions of overlapping and critical parameter values for flow regimes. For example the overlapping of intermittent flow and stratified flow at low liquid superficial velocity can easily cause regime identification errors. On the other hand, in some cases a small change in a critical parameter could trigger change of flow regimes. For example, a change of gas velocity from 12 to 13 can cause the flow regime to change from bubbles to intermittent. As such, identification errors could easily happen due to measurement noise in the gas velocity at these critical values.

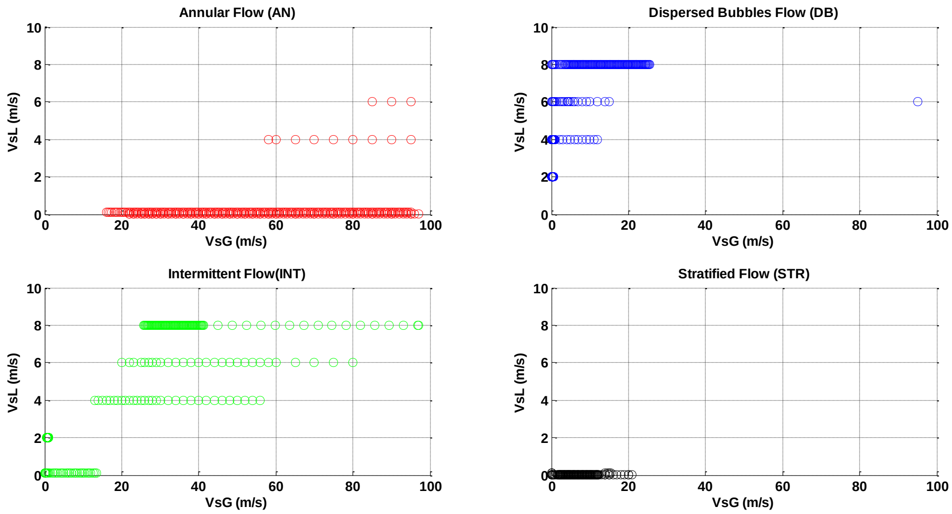

Fig. 2. Regions of the four flow regimes using (V_{sG}, V_{sL}).

For the (dP, HL) pair, the range of the flow regimes is depicted in Fig. 3. Clearly, the situation is much worst with clear overlapping between the stratified and Intermittent at low pressure drop values, and overlapping between Annular and Intermittent at low liquid hold up values.

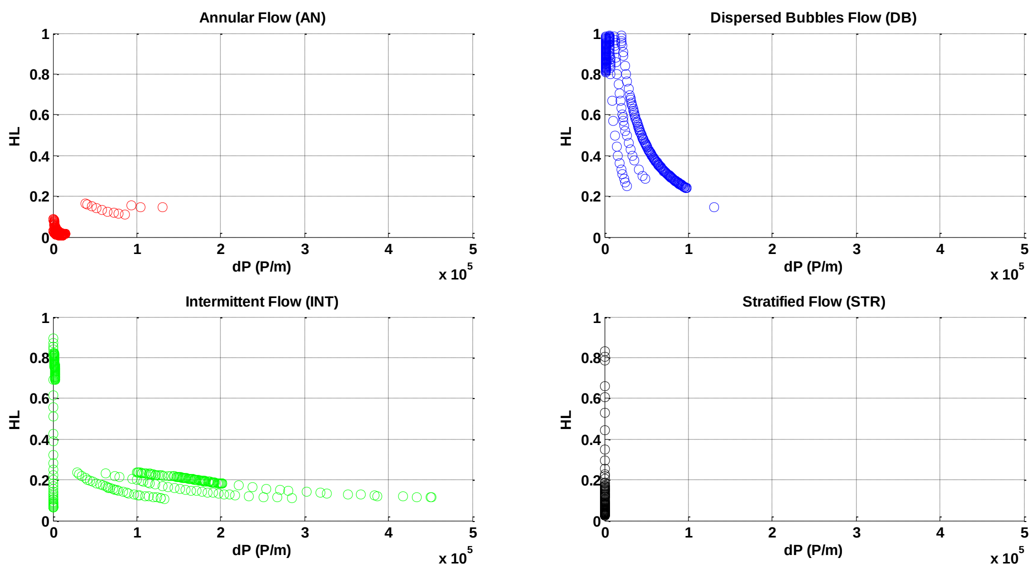

Fig.3. Regions of the four flow regimes using (dP, HL).

Similar behavior was observed when we examined the range of the parameter pairs (ReG, and ReL). Another issue for Reynolds number is unbalance data distribution along large range as shown in Fig.4.

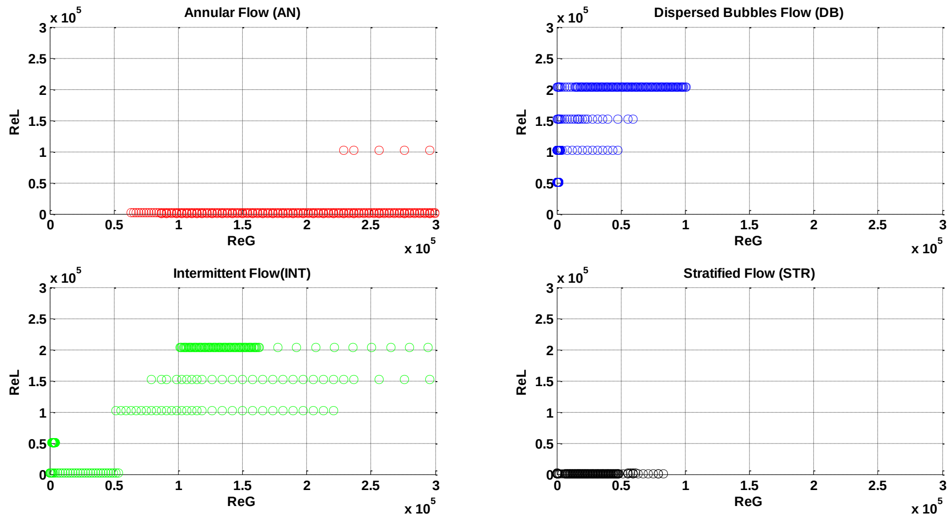

Fig.4. Regions of the four flow regimes using (Re_G, ReL).

Next we studied the possibility of using nonlinear mapping of the flow parameters to improve the separation between the regions of the flow regimes. We report here the result of taking the natural logarithm. Fig. 5 shows the regions of the four flow regimes using Ln (V_{sG}) and Ln (V_{sL}).

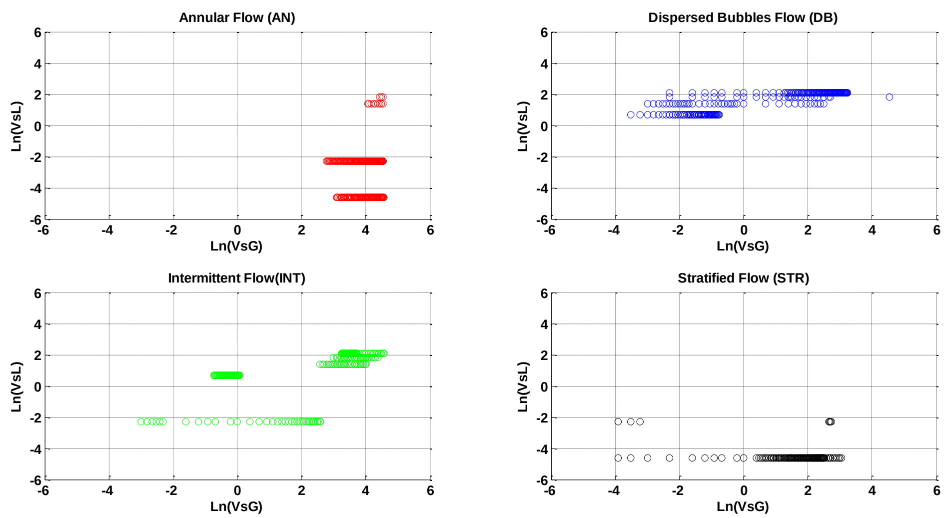

Fig. 5. Regions of the four flow regimes using the natural logarithm of (V_{sG}, V_{sL}).

Fig.6 shows a clear separation of the regions for each of the considered flow regimes. A more impressive result was observed when we considered the (Ln (dP), Ln (HL)) as shown in Fig. 5. In fact, the observed overlapping between Intermitted and Stratified disappeared.

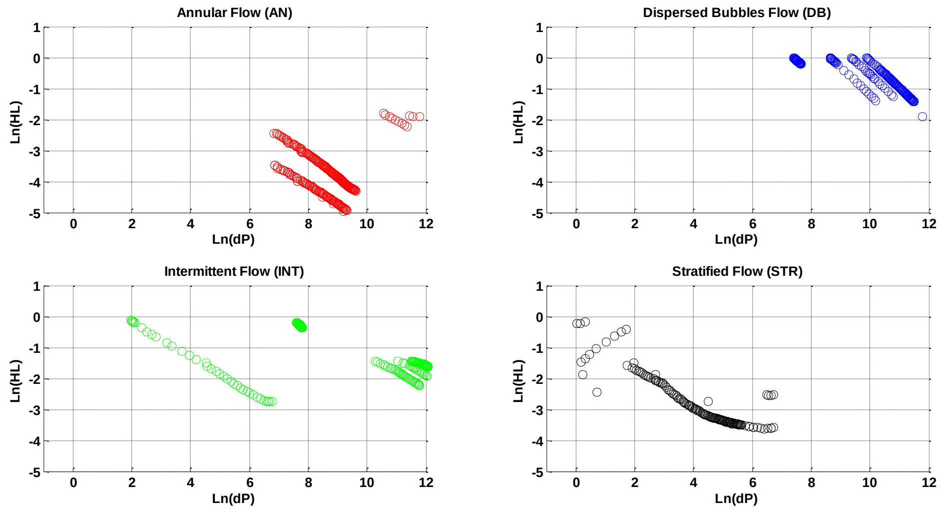

Fig.6. Regions of the four flow regimes using the natural logarithm of (dP, HL).

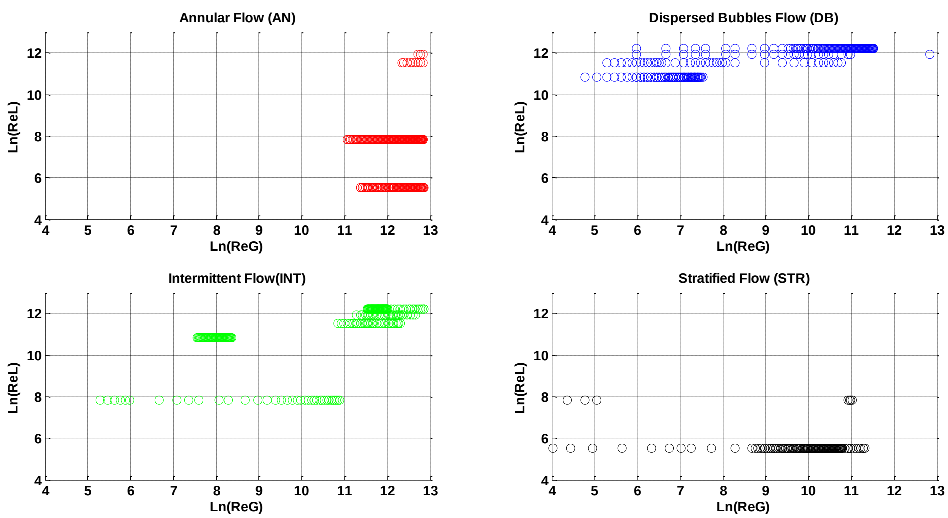

Fig.7. Regions of the four flow regimes using the natural logarithm of (Re_L, Re_G).

In the case of the Reynolds number pairs, the logarithmic mapping not only helps to have better separation between the regions of the regimes, but also provides efficient scaling of the parameter range as shown in Fig.7. Table. 2 shows the results of flow regimes prediction using different configuration of input parameters sets. Improvement in flow regimes identification can be noticed using natural logarithmic of original parameters. For V_{sL} and V_{sG}, the improvement is 3.5 %, for dP and HL is 13.4 % and for Re_L and Re_G is 4.9 %.

Table 2. Percent of correct classification.

	% Correct Classification				
Parameter/ Regime	Annular	Dispersed Bubble	Intermittent	Stratified	Total
V_{sL} , V_{sG}	98.1 %	100.0%	93.9 %	84.0 %	95.1 %
Ln(Vs_L), Ln(Vs_G)	100.0 %	100.0 %	100.0 %	92.0 %	98.6%
dP , HL	88.7 %	96.8 %	81.8%	60.0 %	83.8 %
Ln(dP), Ln(HL)	100.0 %	100.0%	97.1 %	88.0 %	97.2%
Re_L, Re_G	98.1 %	100.0 %	78.8 %	92.0 %	93.0 %
Ln(Re_L), Ln(Re_G)	100.0 %	100.0%	100.0 %	88.0 %	97.9 %

As can be seen in the confusion matrices in Table. 3 based on test data, the first common thing is that confusion is reduced by using natural logarithmic. For Dispersed Bubble, Intermittent and Annular, the confusion is reduced by using the normalized inputs. For Stratified flow, the confusion is reduced in all cases except for the case of Reynold number which slightly less accurate. The results for stratified flow can be improved if the data points can be increased for this flow regimes to make a balance between flow regimes in terms of data points.

Table 3. Incorrect Classification: (a) V_{sL} & V_{sG}, (b) Ln (V_{sL}) & Ln (V_{sG}). (c) dP & HL, (d) Ln (dP) & Ln (HL), (e) Re_L & $Re_{G,}$ (f) Ln (Re_L) & Ln (Re_G).

	% Incorrect Classification			
	AN	DB	INT	STR
AN	---------------	0 %	0%	3.7 %
DB	0 %	---------------	6.1 %	0 %
INT	2.9 %	0 %	---------------	5.9 %
STR	0 %	0 %	0 %	---------------
Total	2.9%	0 %	6.1 %	9.6 %

(a)

	% Incorrect Classification			
	AN	DB	INT	STR
AN	---------------	0 %	0%	3.6 %
DB	0 %	---------------	0 %	0 %
INT	0 %	0 %	---------------	0 %
STR	0 %	0 %	0 %	---------------
Total	0 %	0 %	0 %	3.6 %

(b)

	% Incorrect Classification			
	AN	DB	INT	STR
AN	---------------	0 %	1.7 %	17.2 %
DB	0 %	---------------	3.2 %	0 %
INT	0 %	3.6 %	---------------	0 %
STR	24.0 %	0 %	16.0 %	---------------
Total	24.0 %	3.6 %	20.9 %	17.2 %

(c)

	% Incorrect Classification			
	AN	DB	INT	STR
AN	---------------	0 %	1.8 %	1.8 %
DB	0 %	---------------	0 %	0 %
INT	0 %	0 %	---------------	0 %
STR	0 %	0 %	0 %	---------------
Total	0 %	0 %	1.8 %	1.8 %

(d)

	% Incorrect Classification			
	AN	DB	INT	STR
AN	---------------	0 %	0 %	3.7 %
DB	0 %	---------------	8.8 %	0 %
INT	0 %	0 %	---------------	0 %
STR	3.6 %	0 %	14.3 %	---------------
Total	3.6 %	0 %	23.1 %	3.7 %

(e)

	% Incorrect Classification			
	AN	DB	INT	STR
AN	---------------	0 %	0 %	5.4 %
DB	0 %	---------------	0 %	0 %
INT	0 %	0 %	---------------	0 %
STR	0 %	0 %	0 %	---------------
Total	0 %	0 %	0 %	0 %

(f)

The above results is based on random points selected from the data. Since the transition between flow regimes is one of main the confusion reasons, we need to look to the transition points and show the improvement in this region due to the natural logarithmic normalization. There are 18 data points at the transition between flow regimes in this data set. Table. 4 shows the percentage of misclassified points for each case. Although natural logarithmic does not remove confusion at transition completely but the improvement using natural logarithmic normalization is very clear.

Table. 4. Misclassified percentage at transition region.

Parameters	Percentage of misclassified
V_{sL} , V_{sG}	50 %
$Ln(V_{sL})$, $Ln(V_{sG})$	16.7 %
dP , HL	55.6 %
Ln(dP), Ln(HL)	38.9 %
Re_L, Re_G	38.9 %
$Ln(Re_L)$, $Ln(Re_G)$	22.2 %

5. Conclusion

Flow regimes identification is one of the most difficult tasks in multiphase flow analysis. It is shown that simple nonlinear transformation of multiphase parameters using natural logarithm leads to better scaling and separation of the regions for multiphase regimes. In this work we utilized natural logarithmic to normalize and scale the data for use in simple neural networks with only two inputs for identifications of four flow regimes. The performance of the neural networks showed noticeable improvement over the original parameters. The best results is achieved by using the natural logarithm of the superficial velocities and the natural logarithms of Reynolds numbers. Next step is to test this approach on experimental data to evaluate its performance on noisy data.

Acknowledgement

The authors would like to acknowledge King Fahd University of Petroleum and Minerals for its support in conducting this research work.

References

Bratland O. (2008), Update on Commercially Avaliable Flow Assurance Software Tools: What they can and cannot do?, *4th Asian Pipeline Conference & Exibition*, Kuala Lumpur.

Bratland O. (2009), *Pipe Flow 2, Multiphase flow assurance Book*.

El-Sayed A. (2004), Artificial Neural Network Models for Identifying Flow Regimes and Predicting Liquid Holdup in Horizontal Multiphase Flow, *SPE Production & Facilities*, vol. 19, no. 1, pp.33 - 40.

El-Sebakhy E. A. (2010), Flow Regimes Identification and Liquid-Holdup Prediction in Horizontal Multiphase Flow Based on Neuro-Fuzzy Inference Systems, *Mathematics and Computers in Simulation*, vol. 80, no. 9, pp. 1854–1866.

Murat A., Ertan H. (2012), Analysis of Gas–Liquid Behavior in Eccentric Horizontal Annuli with Image Processing and Artificial Intelligence Techniques, *Journal of Petroleum Science and Engineering*, vol. 81, pp. 31–40.

Rosa E.S., Salgado R.M., Ohishi T., Mastelari N. (2010), Performance Comparison of Artificial Neural Networks and Expert Systems Applied to Flow Pattern Identification in Vertical Ascendant Gas–Liquid Flows, *International Journal of Multiphase Flow*, vol. 36, no. 9, pp. 738–754.

Xiea T., Ghiaasiaana S.M., Karrila S. (2004), Artificial Neural Network Approach for Flow Regime Classification in Gas–Liquid–Fiber Flows Based on Frequency Domain Analysis of Pressure Signals, *Chemical Engineering Science*, vol. 59, no. 11, pp. 2241–2251.

Zhang H.-Q., Wang Q., Sarica C. , Brill J. P. (2003), Unified Model for Gas-Liquid Pipe Flow via Slug Dynamics – Part I: Model Development. *ASME J. Energy Res. Tech.*, vol. 125, no. 12, pp. 266-273

Zhang, H.-Q. Sarica C. (2006), Unified Modeling for Gas/Oil/Water Pipe Flow-Basic Approaches and Preliminary Validation, *SPE J. Project, Facilities & Construction*, vol. 1, no. 2, pp. 1-7.

Taitel Y., Dukler A. E. (1976), A Model for Predicting Flow Regime Transitions in Horizontal and Near Horizontal Gas-Liquid Flow, *AIChE Journal*, vol. 22, no. 1, pp. 47–55.