Escola de Primavera de Transição e Turbulência
Blumenau 2020

ABCM
Associação Brasileira de Engenharia e Ciências Mecânicas

12th Spring School on Transition and Turbulence
September 21st-25th, 2020, Blumenau, SC, Brazil

EPTT-2020-0080
QUANTITATIVE ANALYSIS OF PRESSURE SIGNALS FOR GAS-LIQUID HORIZONTAL FLOW PATTERNS RECOGNITION

Carla Nayara Michels dos Santos
Sarah Laysa Becker
Vinícius Basso de Godoy
Celso Murilo dos Santos
Christine Fredel Boos
Marcela Kotsuka da Silva
Henry França Meier
Chemical Engineering Department, University of Blumenau
Rua São Paulo., 3250, I-303 – 89030-000 – Blumenau – Santa Catarina – Brazil
carlanayara.michels@gmail.com
sarahlaisa@gmail.com
viniciusbassodegodoy@gmail.com
celsomurilo@gmail.com
cfboos@furb.br
marcelakotsuka@furb.br
meier@furb.br

Abstract. *The classification of flow distributions in various patterns is very important for the understanding gas-liquid two-phase flow. Initially flow regimes were defined according to visual observations, which depended on operator interpretation; which is highly subjective. There are currently several objective classification techniques available such as pressure signal analysis, which require simple and robust sensors. The pressure signals corresponding to different biphasic flows present statistical characteristics that can objectively determine flow patterns. The purpose of this study is to identify horizontal flow patterns for pipes using a classification rule based on pressure signal's characteristics. Twelve quantitative parameters were extracted from the pressure signals resulting from an experimental study. The signals were classified in intermittent and stratified flows with smooth and wavy subcategory. Classification rules were based on parameter thresholding. The best rule for stratified/intermittent flow classification achieved 91.16% efficiency for validation data extracted from the experimental unit and 95% efficiency using literature data acquired with different operators, phase velocities and research facilities. The classification rule showed to be a good alternative to blindly diagnose the flow regime based on data from pressure sensors, which are devices that are relatively easy to install, have low cost and are not are intrusive.*

Keywords: *Two-phase flows, gas-liquid flow, flow pattern classification.*

1. INTRODUCTION

Gas-liquid flow presents different spatial distribution of the phases known as flow patterns. These flow patterns bring about numerous possibilities for the interfacial structures in time and space in a given pipe and can be complex with stochastic motion of the phases and intensive fluctuations of local variables (Drahoš and Čermák, 1989). They are result of several parameters that govern the system, such as: gas and liquid flow rates; geometric variables like the tube diameter and angle of inclination; and physical properties of the phases, as the specific masses of gas and liquid, viscosity and surface tension (Mostafa Ghiaasiaan, 2007; Shoham, 2006). The understanding of how phases are distributed and how the behavior of a multiphase system relates to this structure is the central issue in the development of a scientific approach of the gas-liquid flow, since parameters as pressure drop, void fractions, heat transfer rates, mass transfer rates, interfacial stability, residence time distribution, rates of reaction, pressure oscillations, and all other factors behave differently as the flow pattern changes (Rouhani and Sohal, 1983; Taitel and Dukler, 1976; Hanratty et al., 2003).

Different flow pattern maps for two-phase flow have been developed over the years as predictive tools. These maps are based on phase velocities or fluxes, quantification of the homogenous model of a two-phase flow and parameters that include physical properties of the phases (Troniewski and Ulbrich, 1984). They were made mainly for vertical and horizontal pipe orientations but some of them are for inclined pipes (Baker, 1953; Barnea et al., 1982; Golan and Stenning, 1969; Hewitt et al., 1986; Hewitt and Roberts, 1969; Mandhane et al., 1974; Oshinowo and Charles, 1974; Spedding and Nguyen, 1980; Taitel et al., 1980; Taitel and Dukler, 1976; Weisman et al., 1979). The most widely used flow pattern maps mainly represent flow conditions fully developed in tubes with a uniform cross section and are not very accurate in short flow passages (Mostafa Ghiaasiaan, 2007). Many authors report different names for the same flow patterns. In horizontal pipes, the flow regime that occurs is classified into four groups: stratified (smooth and wavy), intermittent (plug or elongated bubble, and slug), annular, and bubbly.

Initially the flow regimes were defined according to visual observations, which depended on operator interpretation making the technique highly subjective. Although there are already techniques such as high-speed camera viewing and image processing that reduce subjectivity, objective and non-invasive or minimally intrusive techniques are of great interest for industry. An example of these techniques is the analysis of pressure signals because the required sensors are simple and robust and the pressure fluctuations resulting from the passage of different two-phase structures have interesting statistical characteristics that can be used for the objective determination of flow patterns (Drahoš et al., 1991).

In addition to pressure, another common parameter related to the flow pattern is the void fraction, which is the relationship between the area occupied by the gas and the total area of the cross section. According to Drahos and Cermak (1989), in vertical pipe flow we can get a close relationship between pressure and void fraction but for horizontal flow this is not so direct and another approach is necessary. However, several authors used pressure signals to identify flow patterns in horizontal pipe flow. Table 1 shows the main authors who used pressure data to characterize gas-liquid flow in horizontal pipes.

Table 1 – Summary of studies on flow patterns identification using pressure signals and a horizontal flow configuration.

Author (year of publication)	**Diameter (mm)**	**Phases**	**Statistical characteristics**
Hubbard and Dukler (1966)	38.1	Air-water	PSD
Weisman et al. (1979)	12; 25; 51	Air-water	Time series, amplitude and frequency
Lin and Hanratty (1987 a;b)	25.4	Air-water	Cross-correlation
Drahos et al. (1987)	50	Air-water	Discriminants based on PDF and PSD
França et al. (1991)	19	Air-water	PDF, PSD and fractal techniques
Cai et al. (1994)	50	Air-water	Kohonen self-organizing map
Drahos et al. (1996)	50	Air - water	Chaotic time series analysis
Wu et al. (2001)	40	Oil-gas-water	Wavelet transform, fractals and ANN
Ding et al. (2007)	15; 25 and 40	Air - water	Hilbert-Huang transform
Santoso et al./ (2012)	24	Air-water	PSD and ANN

Hubbard and Dukler (1966) were the first researchers to analyze pressure fluctuations to try to identify flow patterns in horizontal air-water flow. They developed a method to determine the flow pattern from the Power Spectral Density (PSD) analysis of wall pressure fluctuations. Also based on pressure fluctuations, Weisman et al. (1979) developed of a simple quantitative method for distinguishing between flow patterns in terms of frequency and amplitude. In another approach, Lin and Hanratty (1987a, b) used local pressure data at two different locations instead of pressure drop over a short distance. They used techniques based on the cross-correlation of pressure signals and showed that the transition to a slug condition can be sharply defined.

Drahos et al. (1987) performed a statistical analysis of the wall pressure fluctuations. They suggested ways to detect flow patterns based on quantifying the information contained in the probability density function (PDF) and the PSD frequency domains. França et al. (1991) also calculated a PDF and PSD of pressure signals and used fractal techniques in an attempt to classify the various flow regimes. Although they noted that PSD and PDF might not be the most appropriate parameters for this identification, fractal techniques proved to be a promising way to objectively classify flow patterns. In 1994, Cai et al. applied a Kohonen self-organizing neural network to identify flow regimes. The neural network was trained with stochastic features derived from absolute pressure signals such as standard deviation, coefficient of skewness and kurtosis in the amplitude domain and linear prediction coefficients and prediction residual error in the frequency domain. Drahos et al. (1996) applied methods of deterministic chaos analysis on the wall pressure fluctuations to differentiate between slug and plug flows. Wu et al (2001) analyzed the pressure signals of a three-phase oil-gas-water flow however, for the recognition of the regimes; the authors simplified the flow to two-phase flow. The pressure data was processed with wavelet theory to eliminate noise and then the characteristic vectors of various flow regimes were obtained with fractal theory. These vectors were selected as the input stimuli of a neural network that proved to be a highly accurate and fast technique for flow pattern identification. Ding et al. (2007) applied Hilbert-Huang Transform (HHT) for the dynamic characterization of gas–liquid two-phase flow using a direct relationship between the signal energy distribution and the corresponding flow pattern.

Lastly, as in previous studies performed by Cai et al. (1994) and Wu et al. (2001), Santoso et al. (2012) also used an artificial neural network to identify the flow patterns. In this work, the authors used a statistical analysis of PSD to quantify the characteristics of the pressure signals at different conditions and train the neural network. The accuracy of the identification was 100% to stratified, 100% to plug and 98% to slug flow.

According to earlier works, pressure signals show random fluctuations containing some typical stochastic information about the flow characteristics. This information needs to be quantified and the way it is influenced by the flow regime must be analyzed to allow a proper identification of flow patterns.

The objective of our study is to present and evaluate a method of identifying the flow patterns in short horizontal pipes using a classification rule constructed with a quantitative parameter extracted from differential pressure signals.

2. MATERIALS AND METHODS

2.1 Experimental unit

A schematic representation of the experimental unit used in this work is showed in Fig. 1. The horizontal test section is made of a transparent acrylic tube with inner diameter (D) of 0.074 m and total length (L) of seven meters (L/D ≅ 95).

Geometric variations in the mixing section (gas and liquid inlets) and in the pipe's outlet were applied to verify the generalization of the classification rule in our experimental facility. Atmospheric air and tap water were used as process fluids. The water was injected by a centrifugal pump (Bombetec model BTM-30) coupled to a 2 CV engine (from WEG®) and the air was supplied by a radial compressor (Ibram model CJ4) coupled to a 4 CV engine (from WEG®).

The water and airflow rates were measured by a Venturi meter and orifice plate, respectively. After the experiment, air and water were separated in a gravitational separation tank where the air was exhausted into the atmosphere and the water returns to a reservoir tank.

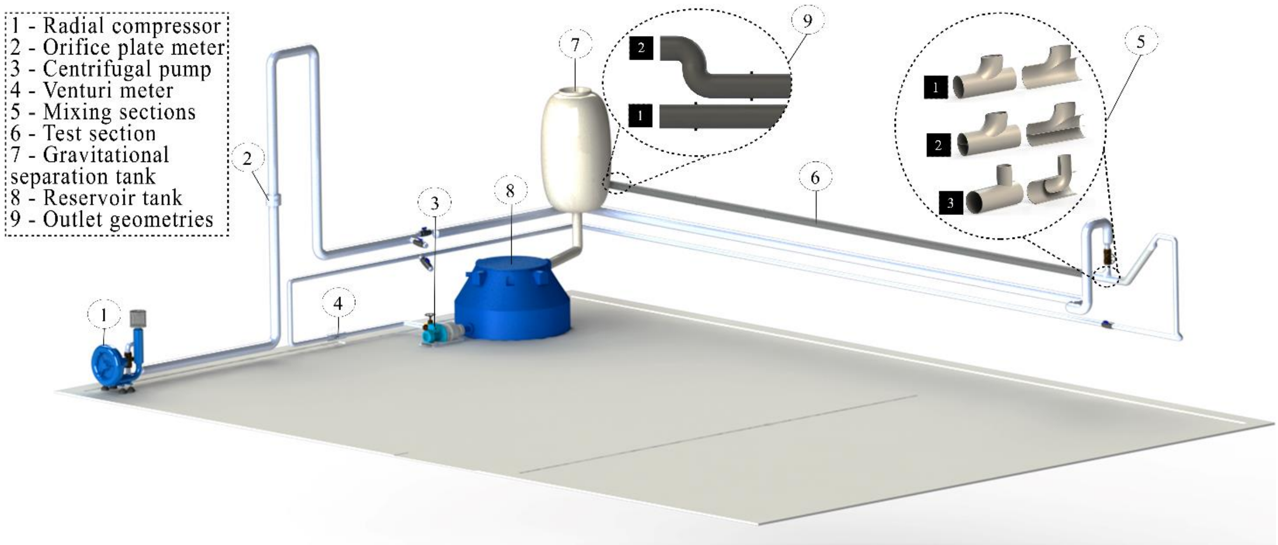

Figure 1 – Schematic representation of the experimental facility

Pressure data was acquired with three differential sensors – Rücken model RTBP-420-DIF with a 0 to 10 kPa measuring range – installed in the horizontal test section. For the analysis of flow development along the pipe the pressure sensors 1, 2 and 3 were respectively installed at 6.8 m (L/D = 65), 5.8 m (L/D = 78.4) and 4.8 m (L/D = 92) from the mixing section. These sensors modulate their pressure range into a 4 to 20 mA linear analog output signal that was acquired at a 1 kHz sampling rate with a USB-6000 National Instruments® board and a virtual instrument developed using LabVIEW® software.

2.2 Experimental data acquisition

The experiments were carried using the superficial phase velocities shown in Tab. 2, for all the possible inlet/outlet geometric configurations of our experimental unit.

To ensure repeatability of the data, each experiment was repeated three times and data was acquired always with the following steps:

- Step 1 – adjust the air supply flow rate;
- Step 2 – adjust the water supply flow rate;
- Step 3 – wait a period of five minutes to ensure the superficial velocities of both phases are stable;
- Step 4 – acquire data for approximately 180 seconds;
- Step 5 – turn off the air and water supply to drain out the pipe.

Table 2 – Superficial phase velocities used on the experiments.

Experiment number	Liquid superficial velocity (m/s)	Gas superficial velocity (m/s)
1	0.10	1.00
2	0.10	5.50
3	0.10	10.00
4	0.55	1.00
5	0.55	5.50
6	0.55	10.00
7	1.00	1.00
8	1.00	5.50
9	1.00	10.00

We observed that the pressure signals had noise from environment electromagnetic interference and due to sensor sensibility. The noisy data was removed using a digital Butterworth low pass fourth order filter, with unit gain and cutoff frequency of 15 Hz. Another digital filter, a second order notch with unit gain, cutoff frequency of 0 Hz and bandwidth of 0.5 Hz, was also used to remove the signal's offset. This second filter was applied because the quantitative analysis we performed is focused on the different baseline fluctuations of the pressure signals.

The experimental signals were divided into 30 seconds segments and the identified flow patterns were randomly separated into groups of data according to the inlet/outlet geometry adopted in the experiments, according Tab. 3. The flow patterns were visually identified based on its specific characteristics described in the established literature on gas-liquid flow (Rouhani and Sohal, 1983; Spedding and Spence, 1993).

The training (TRN) dataset was used to create the classification rules while the verification and validation datasets were used to evaluate the rule's performance. The same operator performed the experiments from training and validation datasets and a different operator used the same experimental unit to acquire the verification dataset signals.

Table 3 – Number of 30 s signal segments contained in the datasets used for flow pattern classification.

Datasets for flow classification	Inlet	Outlet	Stratified smooth flow	Stratified wavy flow	Slug flow	Total
Training (TRN)	1	Without curve	55 signals	18 signals	83 signals	156 signals
Verification (VER)	1	Without curve	73 signals	24 signals	125 signals	222 signals
Validation 1 (VLD_1)	1	With 90° curve	18 signals	55 signals	71 signals	144 signals
Validation 2 (VLD_2)	2	Without curve	54 signals	18 signals	81 signals	153 signals
Validation 3 (VLD_3)	2	With 90° curve	19 signals	57 signals	71 signals	147 signals
Validation 4 (VLD_4)	3	Without curve	18 signals	37 signals	95 signals	150 signals
Validation 5 (VLD_5)	3	With 90° curve	18 signals	36 signals	88 signals	142 signals
		Total:	255 signals	245 signals	614 signals	1,114 signals

2.3 Flow classification

After all data was collected, segmented, filtered and sorted, an algorithm extracted the quantitative parameters used to classify flow regimes. The following 12 parameters related to the signal's morphology were determined using a MATLAB® algorithm:

- AmaxS: Maximum amplitude of the unfiltered signal;
- AmaxC: Maximum amplitude of the filtered signal;
- AmedS: Average amplitude of the unfiltered signal;
- Freq: Prominent frequency of the signal's PSD;
- Freq+AmaxC: Sum of the prominent frequency and maximum amplitude of the filtered signal;
- Freq+AmaxS: Sum of the prominent frequency and maximum amplitude of the unfiltered signal;
- Freq+AmedS: Sum of the prominent frequency and average amplitude of the unfiltered signal;
- Entrp_L: Logarithmic entropy;
- R_AmpS: Amplitude range of the unfiltered signal;
- R_AmpC: Amplitude range of the filtered signal;
- Freq+R_AmpS: Sum of the prominent frequency and the amplitude range of the unfiltered signal;
- Freq+R_AmpC: Sum of the prominent frequency and the amplitude range of the filtered signal.

The flow classification was performed by simply thresholding parameter values and creating a classification rule with an "if … then … else" structure: if *parameter_value* is less than *threshold_value* then the flow pattern is *X*, else the flow pattern is *Y*.

The formulation of the rules started with an exploratory analysis in which the parameter mean value, with its 95% confidence interval, was determined for the three flow patterns observed in the training group (Tab. 3). During this analysis, it was observed that all the parameters had intersecting confidence interval values between the three flow patterns.

However, this behavior was the exact opposite when analyzing the intervals between only stratified and intermittent flows. Consequently, the classification was divided in two parts: first, each signal was classified as stratified or intermittent and then the stratified patterns were classified as either smooth or wavy.

For each parameter, the flow pattern that had the lower mean value was used as the base of the classification rule. For example, if AmaxC's mean value for intermittent flow was lower than the mean value for stratified flow, the classification rule would be: if AmaxC is less than *threshold_value* then the flow pattern is intermittent, else the flow pattern is stratified.

The threshold value was determined by scanning the full value range of each parameter, i.e. from the minimal to the maximal value observed in the data from the training group. All the possible thresholds were applied to the rules and the one that generated the highest classification efficiency was selected.

After all the rules were created for intermittent/stratified and smooth/wavy flow classification using the training dataset these same rules where applied to the remaining datasets for verification and validation of the rules.

Verification data came from the same geometry as the training group, i.e. inlet 1 and outlet without curve, and was extracted from experiments performed by a different operator. Validation data was acquired with different inlet and outlet geometries to check the rule's generalization.

The performance of the rules was based in its average efficiency and standard deviation values for the validation data. Therefore, the best rule was the one with the highest mean efficiency and lower standard deviation.

A final test was performed using data from studies that analyzed pressure signals from horizontal two-phase flow and reported values of the same parameter we found to be the most efficient for quantitative flow classification.

3. RESULTS AND DISCUSSION

Analyzing the flow development, we found that the data from sensor 2 would be the best one for quantitative flow classification because the parameters extracted from the signals acquired at this location (5.8 m) proved to be more stable in a preliminary analysis.

The formulation of the rules started with an assessment of the mean value and its 95% confidence interval for the proposed 12 parameters. Once we established which flow pattern had the smallest average, the next step was the definition of the threshold for classification. The determination of this value was the result of a full range sweep for each parameter and identification of which threshold provided the best separation between the two flow patterns.

After examining the parameters and determining the threshold values for the signals with stratified and intermittent flows, the following rules were created:

- If AmaxS <= 1,897.71 then stratified flow, else intermittent flow.
- If AmaxC <= 255.27 then stratified flow, else intermittent flow.
- If AmedS <= 699.00 then intermittent flow, else stratified flow.
- If Freq <= 1.84 then intermittent flow, else stratified flow.
- If Freq+AmaxC <= 268.84 then stratified flow, else intermittent flow.
- If Freq+AmaxS <= 1910.91 then stratified flow, else intermittent flow.
- If Freq+AmedS <= 275.55 then stratified flow, else intermittent flow.
- If Entrp_L <= 161,838.72 then stratified flow, else intermittent flow.
- If R_AmpS <= 2812.70 then stratified flow, else intermittent flow.
- If R_AmpC <= 513.38 then stratified flow, else intermittent flow.
- If Freq+R_AmpS <= 2824.90 then stratified flow, else intermittent flow.
- If Freq+R_AmpC <= 526.36 then stratified flow, else intermittent flow.

The same assessment for the signals with stratified smooth and wavy flows resulted in following ten rules of stratified flow classification:

- If AmaxS <= 1,166.46 then wavy flow, else smooth flow.
- If AmaxC <= 118.19 then wavy flow, else smooth flow.
- If AmedS <= 102.03 then wavy flow, else smooth flow.
- If Freq <= 1.00 then wavy flow, else smooth flow.
- If Freq+AmaxC <= 123.37 then wavy flow, else smooth flow.
- If Freq+AmaxS <= 1,177.63 then wavy flow, else smooth flow.

- If Freq+AmedS <= 34.00 then wavy flow, else smooth flow.
- If Entrp_L <= 16,1785.00 then smooth flow, else wavy flow.
- If R_AmpC <= 245.16 then wavy flow, else smooth flow.
- If Freq+R_AmpC <= 251.52 then wavy flow, else smooth flow.

There are two less rules for stratified smooth and wavy flow classification because the 95% confidence intervals for R_AmpS and Freq+R_AmpS parameters intersect each other.

The classification performance of the 22 rules was verified using data from the verification dataset, i.e. 156 signals from experiments with inlet 1 and outlet without curve that is the same geometry as the training group. The validation of the rules was performed applying the same rules for the five validation datasets described in Tab. 3. These data were acquired in the experimental unit with changes in the inlet and outlet geometries in order to verify the validity of the rules created when geometric changes are applied. The performance results achieved by the 12 rules for classification of the patterns between intermittent, stratified, and between the stratified smooth and wavy flow are shown in Tab. 4.

Table 4 – Efficiency results of the application of a threshold for the classification between intermittent and stratified flows and between stratified smooth and wavy flows.

Parameters	**Intermittent and stratified flow classification efficiency (%)**			**Stratified smooth and wavy flow classification efficiency (%)**		
	TRN	**VER**	**VLD***	**TRN**	**VER**	**VLD***
AmaxS	99.36	89.64	74.68 (±19.93)	87.67	74.23	32.15 (±28.39)
AmaxC	98.72	91.44	91.02 (±5.58)	90.41	55.67	53.19 (±22.46)
AmedS	53.21	56.31	52.90 (±5.41)	100.00	81.44	38.14 (±21.01)
Freq	87.82	59.91	81.05 (±9.13)	75.34	58.76	33.59 (±29.13)
Freq+AmaxC	98.72	91.44	91.16 (±5.63)	91.78	55.67	49.76 (±25.34)
Freq+AmaxS	99.36	89.64	74.68 (±19.93)	89.04	74.23	32.52 (±27.88)
Freq+AmedS	65.38	43.24	60.44 (±7.28)	75.34	75.26	38.14 (±21.01)
Entrp_L	100.00	91.89	91.14 (±7.15)	75.34	56.70	47.08 (±19.75)
R_AmpS	100.00	88.74	75.25 (±19.72)	–	–	–
R_AmpC	98.08	90.09	90.15 (±6.56)	93.15	50.52	51.01 (±25.07)
Freq+R_AmpS	100.00	88.74	75.25 (±19.72)	–	–	–
Freq+R_AmpC	98.08	90.09	90.15 (±6.30)	93.15	50.52	50.41 (±27.61)

TRN – training dataset; VER – verification dataset; VLD – validation datasets; * average (± standard deviation)

Observing the results of Tab. 4 for the training dataset, it was identified that Entrp_L, R_AmpS and Freq+R_AmpS parameters had 100% efficiency for the classification between stratified and intermittent flow. However, both R_AmpS and Freq + R_AmpS achieved an overall validation efficiency of 75.25% (± 19.72). This large deviation from the average is not a desirable attribute for a generalized classifier. When analyzing Tab. 5, which presents the results achieved by the classification rules for each set of validation data, it is possible to verify the variations in the efficiency values between the validation data, which may represent the effect of the geometric change in the pressure signal in relation to training and verification data. The VLD_3 data set (inlet 2 and outlet with 90 ° curve) was the one with the lowest efficiency values both for the classification rules between the stratified and intermittent flows, as well as for the classification between the smooth and wavy stratified patterns.

The best classification rule was whichever had highest overall validation efficiency with low standard deviation. Five rules had average efficiency higher than 90%. The rules with Freq+AmaxC and Entrp_L had a remarkably similar performance (Tab. 4).

Although one could argue that the 91.14% average efficiency achieved by Entrp_L is close enough to consider its performance matched with the 91.16% of Freq+AmaxC, the standard deviation for the latter is 27% lower. Therefore, the best classification rule was the one using Freq+AmaxC parameter. This rule had 91.16% (±5.63) overall validation efficiency and its application on all datasets is illustrated in Fig. 2. It is possible to verify a clear separation in the dispersion of data between intermittent and stratified flow. Basically, the same dispersion pattern was observed in all data sets.

Table 5 – Efficiency results achieved by the classification rules for each set of validation data.

Parâmetro	Intermittent and stratified flow classification efficiency (%)					Stratified smooth and wavy flow classification efficiency (%)				
	VLD_1	VLD_2	VLD_3	VLD_4	VLD_5	VLD_1	VLD_2	VLD_3	VLD_4	VLD_5
AmaxS	65.97	99.35	48.30	88.67	71.13	24.66	77.78	25.00	0.00	33.33
AmaxC	94.44	96.73	82.31	89.33	92.25	53.42	86.11	28.95	36.36	61.11
AmedS	49.31	52.94	48.30	52.00	61.97	24.66	75.00	25.00	32.73	33.33
Freq	68.75	92.16	80.27	87.33	76.76	6.85	75.00	5.26	34.55	46.30
Freq + AmaxC	94.44	96.73	82.31	89.33	92.96	49.32	86.11	25.00	27.27	61.11
Freq + AmaxS	65.97	99.35	48.30	88.67	71.13	24.66	77.78	25.00	1.82	33.33
Freq + AmedS	62.50	61.44	48.30	68.00	61.97	24.66	75.00	25.00	32.73	33.33
Entrp_L	87.50	100.00	82.99	88.00	97.18	43.84	75.00	57.89	32.73	25.93
R_AmpS	65.97	99.35	48.30	88.00	74.65	-	-	-	-	-
R_AmpC	89.58	99.35	80.95	89.33	91.55	50.68	90.28	27.63	30.91	55.56
Freq + R_AmpS	65.97	99.35	48.30	88.00	74.65	-	-	-	-	-
Freq + R_AmpC	89.58	99.35	81.63	89.33	90.85	49.32	93.06	25.00	27.27	57.41

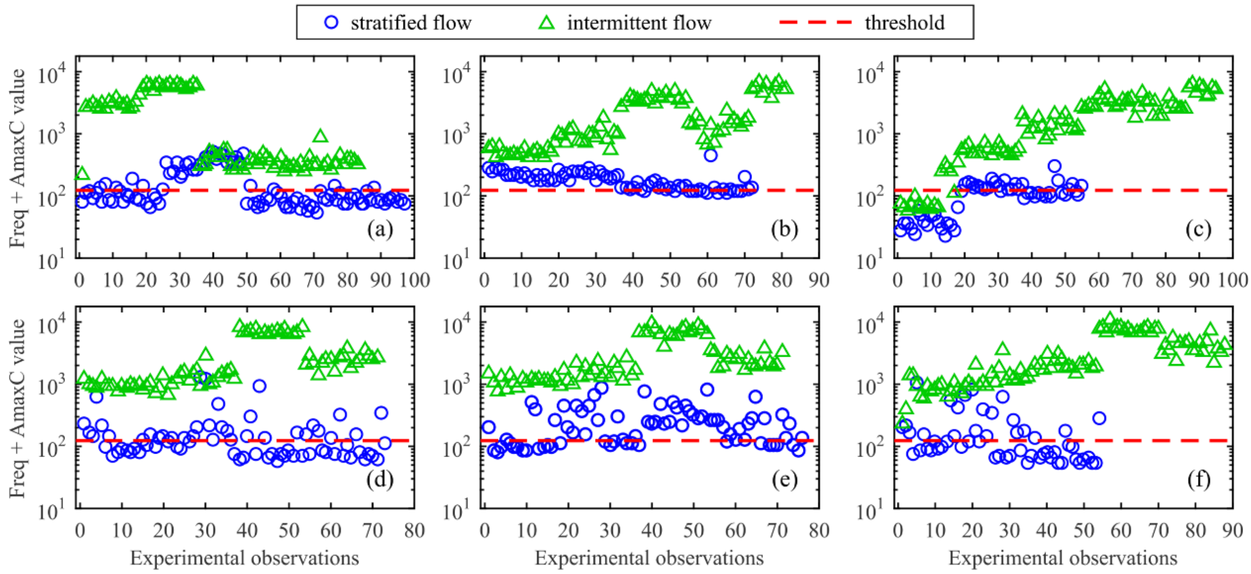

Figure 2 – Intermittent/stratified flow classification rule using Freq+AmaxC parameter. The rule is applied on sensor 2 data from five groups: (a) verification, (b) validation 1, (c) validation 2, (d) validation 3, (e) validation 4 and (f) validation 5.

The performance for stratified smooth/wavy flow classification (Tab. 4) was very poor: 70% of the rules had less than 50% overall validation efficiency. The standard deviation was below 20 in only one classification rule (Entrp_L). Following the proposed criterion, the best parameter to classify between smooth and wavy flow was AmaxC with 53.19% efficiency for the validation dataset.

The pressure parameters provided no distinct separation between the stratified flow patterns (Fig. 3) because the differential pressure signals may not the most adequate to characterize the small wave fluctuations that occurred for the operational conditions used to obtain the stratified flows. Consequently, a classification of stratified flows using differential pressure will have its performance hindered.

The final tests of the classification used data from literature, the relevant information from the five studies found is presented in Tab. 6.

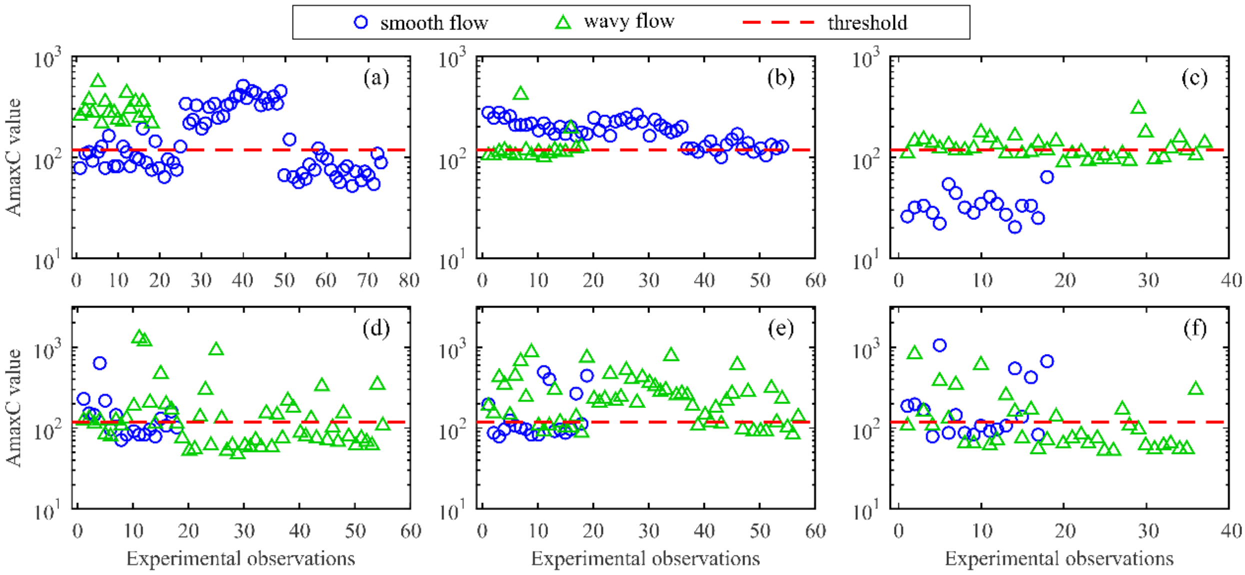

Figure 3 – Stratified smooth/wavy flow classification using AmaxC rule applied on sensor 2 data from (a) verification, (b) validation 1, (c) validation 2, (d) validation 3, (e) validation 4 and (f) validation 5 groups.

Table 6 – Studies on pattern recognition of two-phase air-water flow regimes in horizontal pipes using pressure data that reported both amplitude and prominent frequency of the pressure signals.

Authors	SGV (m/s)	SLV (m/s)	Frequency (Hz)	Amplitude (Pa)	Flow pattern	L (m)	D (mm)
Santoso et al. (2012)	0.255	0.023	19.500	20.000	Smooth	9.000	24.000
Santoso et al. (2012)	0.697	0.438	3.000	297.500	Plug	9.000	24.000
Santoso et al. (2012)	2.315	1.255	2.860	3,867.100	Slug	9.000	24.000
Sun et al. (2012)	NA	NA	22.100	3,352.000	Plug	6.040	50.000
Sun et al. (2012)	NA	NA	4.650	16,530.000	Slug	6.040	50.000
França et al. (1991)	12.600	6.800	5.970	31.730	Wavy	2.926	0.019
França et al. (1991)	0.240	1.100	6.800	95.070	Plug	2.926	0.019
França et al. (1991)	0.990	0.820	5.990	402.330	Slug	2.926	0.019
Drahos et al. (1987)	0.200	0.400	3.690	2,462.000	Smooth/Slug	5.080	50.000
Drahos et al. (1987)	4.000	1.000	0.730	6,418.000	Slug	5.080	50.000
Drahos et al. (1987)	0.750	1.000	2.830	2,493.000	Plug	5.080	50.000
Drahos et al. (1987)	2.000	0.400	0.970	3,399.000	Slug	5.080	50.000
Drahos et al. (1996)	10.000	1.000	1.630	16,509.000	Slug/Annular	5.080	50.000
Drahos et al. (1996)	15.000	1.000	1.840	19,971.000	Slug/Annular	5.080	50.000
Drahos et al. (1996)	20.000	1.000	3.130	8,354.000	Slug/Annular	5.080	50.000
Drahos et al. (1996)	6.000	1.000	1.430	13,335.000	Slug	5.080	50.000
Drahos et al. (1996)	0.500	1.000	3.000	1,573.000	Bubble/Plug	5.080	50.000
Drahos et al. (1996)	0.750	1.000	3.000	1,952.000	Plug	5.080	50.000
Drahos et al. (1996)	1.000	1.000	1.000	1,963.000	Plug/Slug	5.080	50.000
Drahos et al. (1996)	1.500	1.000	0.860	2,708.000	Slug	5.080	50.000

SGV – superficial gas velocity; SLV – superficial liquid velocity; L – length of the pipe; D – diameter of the pipe; NA – data not available.

Considering that not all studies used the same flow pattern map, the reported phase superficial velocities were used to identify the location of the experiments on the map of Mandhane et al. (1974). The flow patterns adopted for the literature-based classification test are indicated on Fig. 4. There was one difference when compared the flow patterns identified on the map and those reported in the studies. França et al. (1991) reported that the experiment with 12.6 m/s gas and 6.8 liquid velocities was a stratified wavy flow while according to Mandhane's map; this experiment should have a bubble flow. Since the superficial velocities of Sun et al. (2012) were not available and the flow pattern from França et al. (1991) was, different it was used the patterns reported by both authors instead of using the one indicated by Mandhane's map.

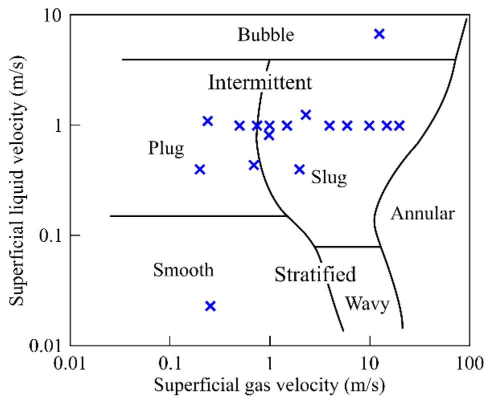

Figure 4 – Selected studies (Tab. 5) experimental points on the flow pattern map of Mandhane et al. (1974).

Classification of literature data using Freq+AmaC rule is shown in Fig. 5. Only one experimental point was misclassified resulting in 95% efficiency. The rule falsely identified the flow pattern with gas/liquid operational condition of 0.24/1.10 m/s as stratified instead of intermittent. Moreover, even if we had excluded França et al. (1991) divergent data the performance could still be considered good with 94.74% efficiency.

The sole misclassification with literature data can be explained by the lack of intermittent plug patterns in the training group. Since no plug flow operational conditions occurred in the experiments, the classifier had no examples of the parameter values for this pattern and consequently had a deficiency in its generalization power. One way to correct this is to extend the levels of the experimental test matrix to incorporate plug flow operational conditions. However, this could only be done by updating the experimental unit to allow the operating conditions for the occurrence of this flow pattern.

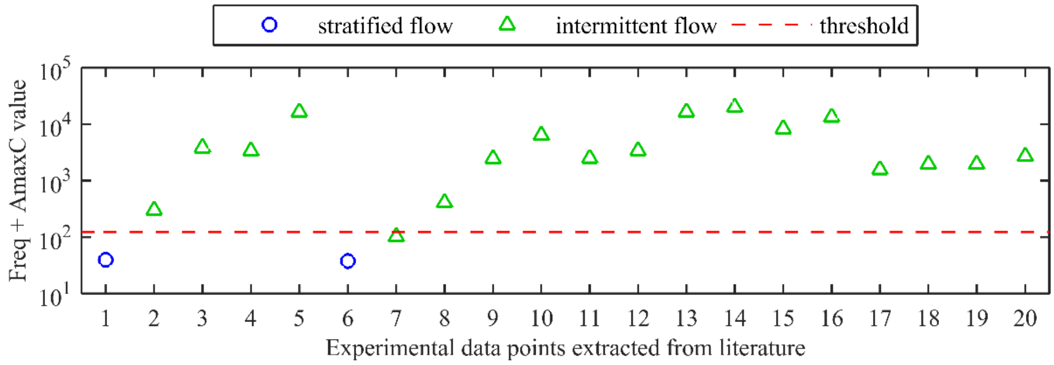

Figure 5 – Result of the application of Freq+AmaxC rule on data from selected studies (Tab. 5).

4. CONCLUSIONS

Analyzing the rules for the classification of flow patterns, the parameter Freq+AmaxC proved to be quite promising. It showed an average efficiency of 92.28% achieved for training, verification and validation datasets extracted from the experimental unit located at the Verification and Validation Laboratoty. The comparison of the results obtained with literature data were also good since this rule had a 95% performance using data acquired by different operators, gas-liquid velocities and at different research facilities.

This method of identifying the stratified and intermittent flow patterns proves to be a good alternative for the industry's necessity to blindly diagnose the flow regime based on data from pressure sensors because these devices are relatively easy to install, have a low cost and are not intrusive of the flow.

However, this classification methodology still has room for improvement. More experiments can be added to the training dataset to incorporate not only the other regimes such as bubble and annular flows, but also different examples of stratified and intermittent flows. It is also important that data from different experimental units be integrated into the training dataset to consider any possible inlet/outlet geometry effect on the signal's parameters.

5. ACKNOWLEDGEMENTS

This work was supported by Coordenação de Aperfeiçoamento de Pessoal de Nível Superior (CAPES); Conselho Nacional de Desenvolvimento Científico e Tecnológico (CNPq); and Petrobras [grant number 5850.0103010.16.9].

6. REFERENCES

Baker, O., 1953. Design Of Pipelines for the Simultaneous Flow Of Oil and Gas. Fall Meet. Pet. Branch AIME 323-G.

Barnea, D., Shoham, O., Taitel, Y., 1982. Flow pattern transition for vertical downward two phase flow. Chem. Eng. Sci. 37, 741–744.

Cai, S., Toral, H., Qiu, J., Archer, J.S., 1994. Neural network based objective flow regime identification in air-water two phase flow. Can. J. Chem. Eng. 72, 440–445.

Ding, H., Huang, Z., Song, Z., Yan, Y., 2007. Hilbert-Huang transform based signal analysis for the characterization of gas-liquid two-phase flow. Flow Meas. Instrum. 18, 37–46.

Drahoš, J., Čermák, J., 1989. Diagnostics of gas-liquid flow patterns in chemical engineering systems. Chem. Eng. Process. 26, 147–164.

Drahoš, J., Čermák, J., Selucký, K., Ebner, L., 1987. Characterization of hydrodynamic regimes in horizontal two-phase flow. Part II: Analysis of wall pressure fluctuations. Chem. Eng. Process. 22, 45–52.

Drahoš, J., Tihon, J., Serio, C., Lübbert, A., 1996. Deterministic chaos analysis of pressure fluctuations in a horizontal pipe at intermittent flow regime. Chem. Eng. J. Biochem. Eng. J. 64, 149–156.

Drahoš, J., Zahradník, J., Punčochář, M., Fialová, M., Bradka, F., 1991. Effect of operating conditions on the characteristics of pressure fluctuations in a bubble column. Chem. Eng. Process. 29, 107–115.

Ebner, L., Drahoš, J., Ebner, G., Čermák, J., 1987. Characterization of hydrodynamic regimes in horizontal two-phase flow Part I: Pressure drop measurements. Chem. Eng. Process. 22, 39–43.

Franca, F., Acikgoz, M., Lahey, R.T., Clausse, A., 1991. The use of fractal techniques for flow regime identification. Int. J. Multiph. Flow 17, 545–552.

Golan, L.P., Stenning, A.H., 1969. Two-Phase Vertical Flow Maps. Proc. Inst. Mech. Eng. Conf. Proc. 184, 108–114.

Hanratty, T.J., Theofanous, T., Delhaye, J.M., Eaton, J., McLaughlin, J., Prosperetti, A., Sundaresan, S., Tryggvason, G., 2003. Workshop on Scientific Issues in Multiphase Flow. Int. J. Multiph. Flow 29, 1042–1116.

Hewitt, F., Delhaye, M., Zuber, N., 1986. Multiphase Science and Technology, Volume 2., Multiphase Sci and Tech.

Hewitt, G.F., Roberts, D.N., 1969. Studies of Two-Phase Flow Patterns by Simultaneous X-Ray and Flash Photography. United Kingdom Atomic Energy Authority Report AERE-M 2159.

Hubbard, M.G., Dukler, A.E., 1966. The characterization of flow regimes for horizontal two-phase flow, in: Saad, M.A., Moller, J.A. (Eds.), Proceedings of the Heat Transfer and Fluid Mechanics Institute. Stanford: Stanford University Press.

Kruskal, W.H., Wallis, W.A., 1952. Use of Ranks in One-Criterion Variance Analysis. J. Am. Stat. Assoc. 47, 583–621.

Lin, P. Y., Hanratty, T.J., 1987. Detection of slug flow from pressure measurements. Int. J. Multiph. Flow 13, 13–21.

Lin, P Y, Hanratty, T.J., 1987. Effect of pipe diameter on flow patterns for air-water flow in horizontal pipes 13, 549–563.

MacFarland, T.W., Yates, J.M., 2016. Kruskal–Wallis H-Test for Oneway Analysis of Variance (ANOVA) by Ranks, in: Introduction to Nonparametric Statistics for the Biological Sciences Using R. Springer International Publishing, Cham, pp. 177–211.

Mandhane, J.M., Gregory, G.A., Aziz, K., 1974. A flow pattern map for gas-liquid flow in horizontal pipes. Int. J. Multiph. Flow 1, 537–553.

Massey, F.J., 1951. The Kolmogorov-Smirnov Test for Goodness of Fit. J. Am. Stat. Assoc. 46, 68.

Mostafa Ghiaasiaan, S., 2007. Two-phase flow, boiling and condensation: In conventional and miniature systems, Two-Phase Flow, Boiling and Condensation: In Conventional and Miniature Systems.

Oshinowo, T., Charles, M.E., 1974. Vertical two-phase flow part I. Flow pattern correlations. Can. J. Chem. Eng. 52, 25–35.

Richardson, J.T.E., 2018. Kruskal–Wallis Test, in: Frey, B.B. (Ed.), The SAGE Encyclopedia of Educational Research, Measurement, and Evaluation. SAGE Publications, Inc., 2455 Teller Road, Thousand Oaks, California 91320, pp. 937–939.

Rouhani, S.Z., Sohal, M.S., 1983. Two-phase flow patterns: A review of research results. Prog. Nucl. Energy 11, 219–259.

Santoso, B., Indarto, Deendarlianto, Thomas, S.W., 2012. The identification of gas-liquid co-current two phase flow pattern in a horizontal pipe using the power spectral density and the artificial neural network (ANN). Mod. Appl. Sci. 6, 56–67.

Shoham, O., 2006. Mechanistic Modeling of Gas-Liquid Two-Phase Flow in Pipes. Soc. Pet. Eng. 2006.

Spedding, P.L., Nguyen, V.T., 1980. Regime maps for air water two phase flow. Chem. Eng. Sci. 35, 779–793.

Spedding, P.L., Spence, D.R., 1993. Flow regimes in two-phase gas-liquid flow. Int. J. Multiph. Flow 19, 245–280.

Sun, Z., Chen, Y., Gong, H., 2012. Classification of gas-liquid flow patterns by the norm entropy of wavelet decomposed pressure fluctuations across a bluff body. Meas. Sci. Technol. 23.

Taitel, Y., Bornea, D., Dukler, A., 1980. Modelling Flow Pattern Transitions for Steady Upward Gas-Liquid Flow in Vertical Tubes. AIChE J. 26, 345–354.

Taitel, Y., Dukler, A.E., 1976. A model for predicting flow regime transitions in horizontal and near horizontal gas-liquid flow. AIChE J. 22, 47–55.

Theodorsson-Norheim, E., 1986. Kruskal-Wallis test: BASIC computer program to perform nonparametric one-way analysis of variance and multiple comparisons on ranks of several independent samples. Comput. Methods Programs Biomed. 23, 57–62.

Troniewski, L., Ulbrich, R., 1984. The analysis of flow regime maps of two-phase gas-liquid flow in pipes. Chem. Eng. Sci. 39, 1213–1224.

Weisman, J., Duncan, D., Gibson, J., Crawford, T., 1979. Effects of Fluid Properties and Pipe Diameter on Two- Phase Flow Patterns in Horizontal Lines. Int. J. Multiph. Flow 5, 437–462.

Wu, H., Zhou, F., Wu, Y., 2001. Intelligent identification system of flow regime of oil-gas-water multiphase flow. Int. J. Multiph. Flow 27, 459–475.

7. RESPONSIBILITY NOTICE

The authors are the only responsible for the printed material included in this paper.