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Three-Phase Flow-Rate Measurement by Pressure Transducers

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ABSTRACT

A multiphase flowmetering technique based on characterisation, classification and identification of pressure signals has been developed and tested in oil-water-air slug flow. The technique extracts a set of stochastic features from pressure signals and relates these to water-cut and liquid and gas flowrate by training back-propagation neural networks with calibration samples. Laboratory tests in 3 inch and 4 inch horizontal three-phase flow over a wide range of flow conditions have shown a measurement accuracy of +/- 10% for liquid-gas flowrates and +/- 5% for water-cuts.

INTRODUCTION

Significant pressure and phase concentration fluctuations are known to occur in multiphase flows. These can be detected readily by common transducers which can operate with a matching frequency response. A number of qualitative studies of stochastic methods are encountered in the literature in which pressure and void-fraction waveforms were applied for flow-regime discrimination [1-5].

Recently, a software based technique[6-9] (named ESMER) was developed at Imperial College for the identification of individual phase flowrates from pressure fluctuation characteristics in water-air flow. Figure 1 shows the broad principles of the technique. A set of stochastic features, which are uniquely related to water and air flowrate, are extracted from absolute and differential pressure signals (tappings were configured axially and radially). A set of experimental data comprising superficial velocities of the individual phases and the related feature sets are saved in a calibration database. The calibration database is then applied in an on-line flow rate measurement system which works by identifying the best match between the measured feature set and those in the calibration database.

The ESMER technique relies on the creation of distinct and reproducible flow patterns at given liquid and gas flowrates. It is well known that distinct flow patterns are also created in oil-water-gas flow around given ranges of flowrates and phase mixtures. A number of tests conducted on 3 and 4 inch diameter pipelines have shown that certain features are more sensitive to water-cut. Features were found to exhibit different degrees of sensitivity to water-cut and liquid-gas flowrate. This is a promising indication of the possibility of the extension of ESMER technique to three-phase flow measurement. However, due to the greater complexity of three-phase flow patterns, the feature sets and pattern recognition techniques must be more finely selected and tuned. This paper presents the extension of the ESMER technique for three-phase flowrate measurement.

THEORETICAL BACKGROUND

In-situ Calibration

Features derived from pressure signals have been found to be affected by a number of variables. These can be

References and illustrations at end of paper categorised as follows:

- *Hydrodynamic quantities:* flowrate, density ratio, physical properties such as viscosity and surface tension;
- *Flow line geometry:* upstream conditions, diameter, orientation;
- *Instrumentation:* sensor location and configuration, signal acquisition parameters such as sampling frequency and period.

In the present series of laboratory tests, all variables were kept constant with the exception of oil, water and gas flowrates.

Feature Selection

Considering oil and water to form a liquid phase having average mixture physical properties, measurement variables can be defined as water-cut and liquid and gas flowrates. The first task is to distinguish between water-cut sensitive features and flowrate sensitive features.

- *Water-cut sensitive features*

Water-cut sensitive features are strongly responsive to water-cuts but little affected by liquid-gas flowrates. Feature sets obtained under a range of liquid and gas flowrates at a given water-cut should group closely in the multi-dimensional feature space while distancing themselves from those at other water-cuts. Calibration measurements should be made for a number of flowrates at each water-cut.

- *Liquid and gas flowrate sensitive features*

Flowrate sensitive features are strongly responsive to flowrates but little affected by water-cuts. A calibration database consisting of the flowrate sensitive features and superficial liquid and gas velocities can be constructed from data obtained at a number of grid points in the superficial liquid-gas velocity map regardless of water-cuts. The database can be used for flowrate identification irrespective of water-cut.

Pattern Recognition

The back-propagation neural network has been successfully applied in solving many pattern recognition problems which had proven difficult for traditional methods[10-15]. To enhance the pattern recognition capability, an identification scheme (Figure 2) was proposed where the back-propagation neural network was applied for learning the mapping function between features and the measurement variables.

The network comprises an input layer (input vector), hidden layers and an output layer (output vector). Units (neurons) in these layers are interconnected with weights. The number of hidden layers and the neuron number in each layers are the parameters required for the network architecture. In our application, the input vector is equivalent to a set of stochastic features and output vector to water-cut or liquid and gas flowrate.

The network learns the mapping function by entering associated input and target output values from calibration data set repeatedly, making changes in its weights in a direction to minimise the sum of squared errors between its prediction outputs and target outputs. This procedure is termed network training. The resulting network model is tested by feeding samples which have not been used in the preceding training process. If similar accuracy is achieved, the network is considered to possess the capability to generalise and it can then be used for measurement.

LABORATORY TESTS

Experiments

Experiments were conducted in 3 inch and 4 inch horizontal multiphase pipelines. Diesel oil, water and air were employed as the component fluids. Pressure transducers, comprising absolute, axial differential and radial differential tappings were mounted in the flowlines with an upstream straight length of around 6m for the 3 inch pipeline and of around 15m for the 4 inch pipeline.

Pressure signals were collected at a sampling frequency of 40Hz and a sampling period of 102.4S, comprising 4096 points per sample record. Water-cut levels employed in the series were 0, 10, 20, 35, 50 and 75%, and liquid and air superficial velocities ranges were 0.36 - 1.8 m/s and 0.88 - 4.9 m/s in the 3 inch pipeline and 0.30 - 1.1 m/s and 1.0 - 2.9 m/s in the 4 inch pipeline, respectively. Visual observation confirmed that the flow pattern was in the slug flow regime. 48 measurements were taken at each water-cut comprising different combinations of liquid and air flowrates.

Water-cut Measurement

Radial differential pressure signals were used to derive linear prediction coefficients[16]. In this study, the signal is modelled as a linear combination of its past four values. It was found that the linear prediction coefficients (a1, a2, a3, a4) and the residual error coefficient (Ep) were sensitive to water-cuts. Figure 3 shows a data set including a number of water-cut classes in the (Ep, a2) two-dimensional feature space. Samples belonging to each water-cut were seen to be clustered closely.

The network was designed to comprise an input layer with 5 neurons, features a1,a2,a3,a4,Ep; a hidden layer with 8 neurons; and an output layer with a single neuron, the water-cut. The calibration data set comprised measurement samples at water-cut levels of 0%, 10%, 35%, and 50% with each water-cut having 24 combinations of flowrates. The network was trained successfully.

Tests were conducted with a data set comprising 24 samples at each of 0%, 10%, 20%, 35%, 50% water-cuts. These shows that +/-5% accuracy level can be achieved (Figure 4). The high measurement accuracy obtained for 20% water-cut suggests that water-cuts which are outside the calibration data set can be identified.

<u>Liquid and Gas Flowrate Measurement</u>

The following flowrate sensitive features were derived from absolute and axial differential pressure signals.

(i) Standard deviation of a temporal differential signal

Let $AP(t)$ represent an absolute pressure signal, then a temporal differential signal $X(t,t_0)$ can be obtained by,

$$X(t,t_0) = AP(t) - AP(t-t_0) \qquad ...(1)$$

where t_0 = the time lag.

We calculated the standard deviation (*Sd*) of $X(t,t_0)$ and found that within a certain range of t_0, *Sd* was a flowrate sensitive feature. Figure 5 shows the contour maps of *Sd* (t_0 = 0.1S) for 35% and 75% water-cuts. In this study four features were derived for t_0 = 0.1, 0.2, 0.3 and 0.4 second.

(ii) Fraction of time above an amplitude threshold

From the axial differential pressure signal, we calculated the fraction of time *Tc* while the amplitude of the signal remained above a given threshold level, *C*. Figure 6 shows that the feature *Tc* at *C* = 5 mbar is very sensitive to the liquid flowrate and two different water-cuts exhibit similar feature maps. Two features were derived for *C* = 5 and 10 mbar.

The input values to the network were the six features described earlier and the target outputs were chosen as the superficial liquid and gas velocities. A single hidden layer with 8 neurons was employed.

Tests were conducted with 3 inch and 4 inch data, respectively. For each pipeline diameter, a training data set was created from 48 measurement samples obtained at 35% water-cut. The testing data set for each case contained 48 samples whose water-cuts were selected randomly from 0%, 10%, 20% , 50% and 75%. Figures 7 and 8 show the measurement accuracy on 3 inch and 4 inch flowlines, respectively. Within the range of tests, errors of both liquid and gas were confined within +/- 10%. The error was calculated as follows:

$$\varepsilon = (v_m - v_a) \times 100\% / (v_{\max} - v_{\min}) \qquad ...(2)$$

where v_m = measured superficial velocity; v_a = actual superficial velocity; and $v_{\max}$, $v_{\min}$ = maximum and minimum actual superficial velocity, respectively.

CONCLUSIONS

1. A software based multiphase flowrate and water-cut measurement technique is developed that utilises ordinary pressure transducers which can be installed and maintained at low cost. The technique was tested in the laboratory under horizontal slug flow conditions.

2. A group of stochastic features sensitive to water-cuts and liquid-gas flowrates were derived from pressure signals obtained in the slug flow regime. The back-propagation neural network was employed for establishing the relationship between the feature sets and the corresponding water-cuts and liquid-gas flowrates.

3. With in-situ calibration, liquid-gas flowrates could be measured with +/- 10% accuracy and water-cuts could be identified with +/- 5% accuracy.

4. Further three phase data are required to generalise the conclusions reached from this specific data set. This may require extracting more features and replacing the superficial co-ordinates by dimensionless variables.

NOMENCLATURE

a1,a2,a3,a4 = linear prediction coefficients
C = amplitude threshold level
Ck = coefficient of kurtosis
Cs = coefficient of skewness
Ep = residual error coefficient in the linear prediction
Sd = standard deviation
Tc = fraction of time above an amplitude threshold
t_0 = time lag of the temporal differential signal

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REFERENCES

1. Taitel, Y. and Dukler, E.: "A Model for Predicting Flow Regime Transition in Horizontal and near Horizontal Gas-Liquid Flow," AIChE J.(1976), 22, no. 1, 47-55

2. Matsui, G.: "Identification of Flow Patterns in Horizontal Gas-Liquid Two-phase Flow Using Differential Pressure Fluctuations," Int. Sympo. on Fluid Control & Measurement, Tokyo, Japan (1985)

3. Sekogushi, K., Inoue, K. and Imasaka, T.: "Void Signal Analysis and Gas-Liquid Two-phase Flow Regime Determination by a Statistical Pattern Recognition Method," JSME Int. J. (1987), 30, 1266-1273

4. King, C.H., Ouyang, M.S. and Pei, B.S.: "Identification of Two- phase Flow Regimes by an Optimum Modelling Method," Nuclear Technology (1988), 82, 211-226

5. Lu, Z.Q. and Wang, M.J.: "Application of Statistical Pattern Recognition Method to Identification of Two-phase Flow Pattern and the Transition," Proc. Int. Conf. Multi-phase Flows, Tsukuba, Japan (1991), 33-36

6. Darwich, T., Toral, H. and Archer, J.S.: "An Expert System for Multi-phase Measurement and Regime Identification," Paper SPE 19136 Presented at the SPE Petroleum Computer Conf., Lake Conroe, TX (1989)

7. Toral, H., Beg, N. and Archer, J.S.: "Multi-phase Flowmetering by Software," Int. Conf. on Basic Principles & Indust. Appli. of Multi-phase Flow, London (1990)

8. Darwich, T.D., Toral, H. and Archer, J.S.: "A Software Technique for Flowrate Measurement in Horizontal Flow," SPE Production Engineering (August 1991), 265-270

9. Beg, N. and Toral, H.: "A Two-Phase Flowrate Measurement Technique in Horizontal Pipes with Off-Situ Calibration," Intl. J. of Multi-phase Flow (in press)

10. Burr, D: "Experiments with a Connectionist Text Reader," Proc. First Intl. Conf. Neural Networks, San Diego (1987), IV-717 - IV-724

11. Lippman, R.P.: "An Introduction to Computing with Neural Nets," IEEE ASSP Magazine (April 1987)

12. Dietz, W., Kirch, E., and Ali, M.: "Jet and Rocket Engine Fault Diagnosis in Real Time," J. Neural Network Computing (Summer,1989), 5-18

13. Yoon, Y., Brobst, R., Bergstresser, P., Peterson, L.: "A Desktop Neural Network for Dermatology Diagnosis," J. of Neural Network Computing, 1 (summer, 1989), 43-52

14. Malferrari, L., Serra, R., and Valastro, G.: "An Application of Neural Networks to Oil Well Drilling," Proc. Intl. Neural Networks Conf., Paris (1990) , 127-130

15. Vierhinathan, J., and Wagner, D.: "A neural Network Approach to First Break Picking", Proc. Third Intl. Joint Conf. Neural Networks, San Diego (1990), I-235-I-240

16. Makhoul, J.: "Linear Prediction: a Tutorial Review," Proc. IEEE (1975), Vol. 63, 561-580

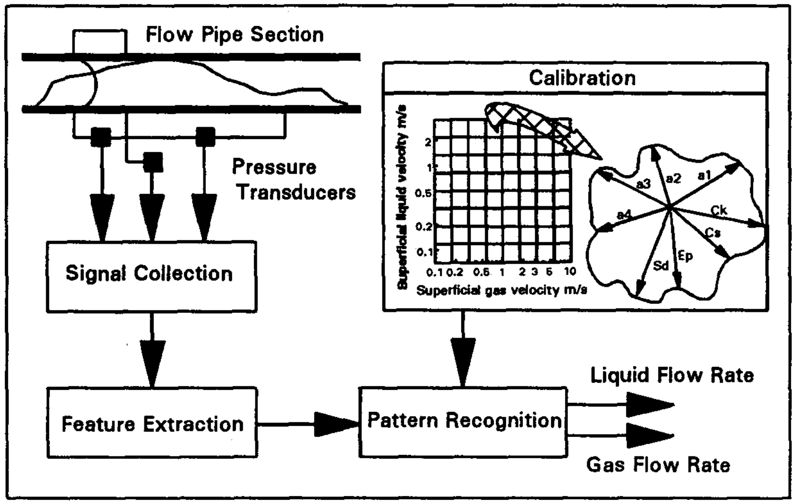


Figure 1. ESMER Schematic

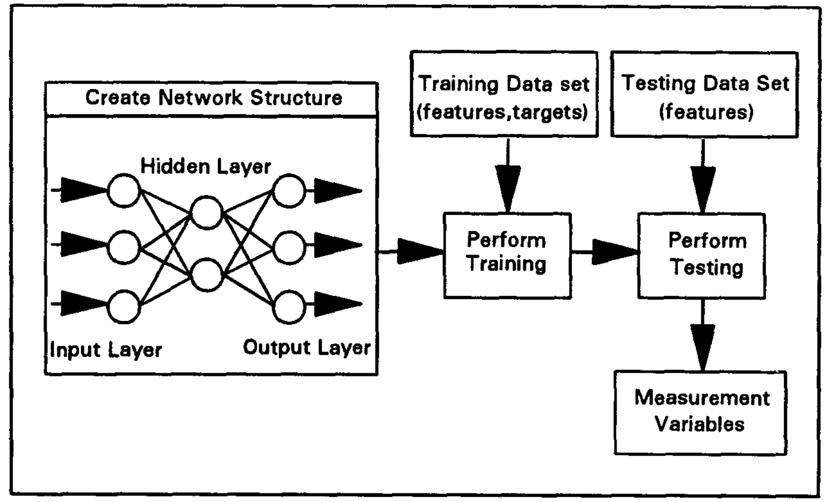


Figure 2. Identification Scheme by Back-Propagation Neural Network

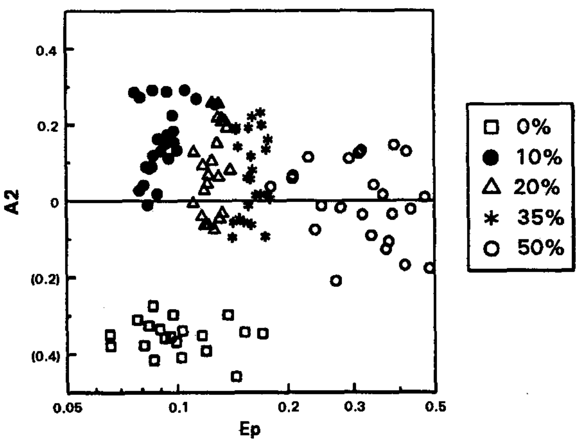


Figure 3. The clustering of Water-cut samples
In the (Ep,A2) Feature Space (3 inch Pipeline)

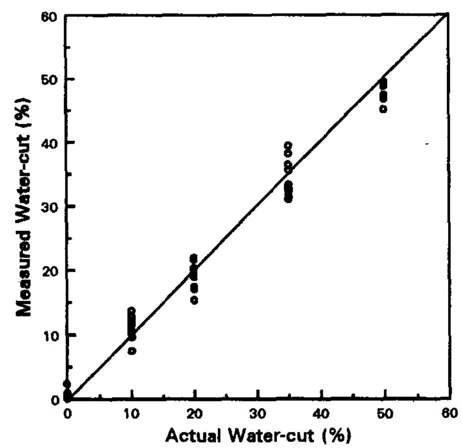
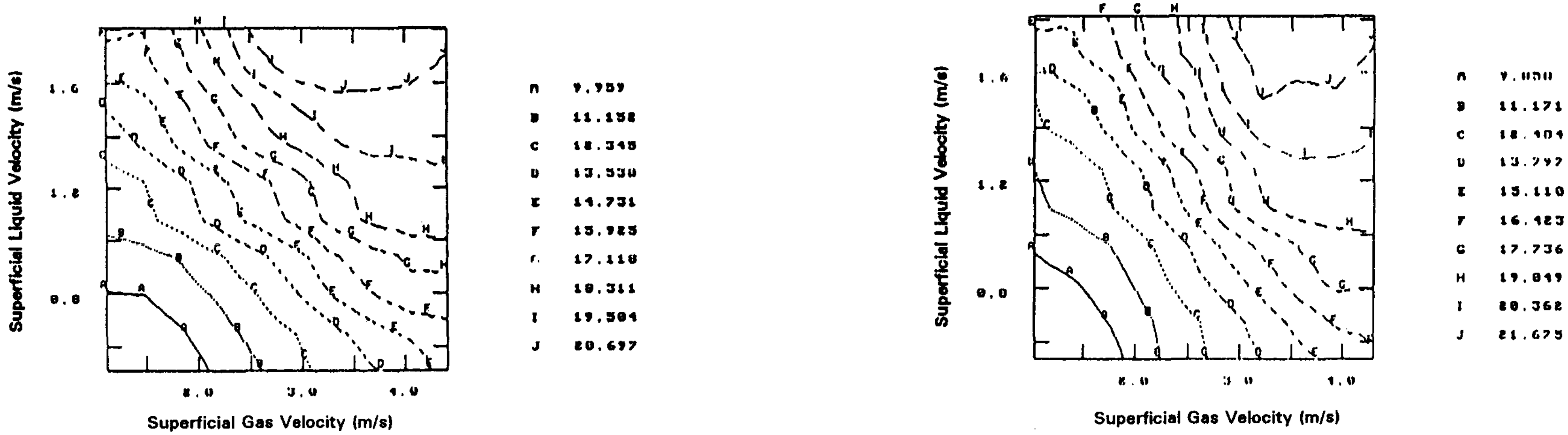


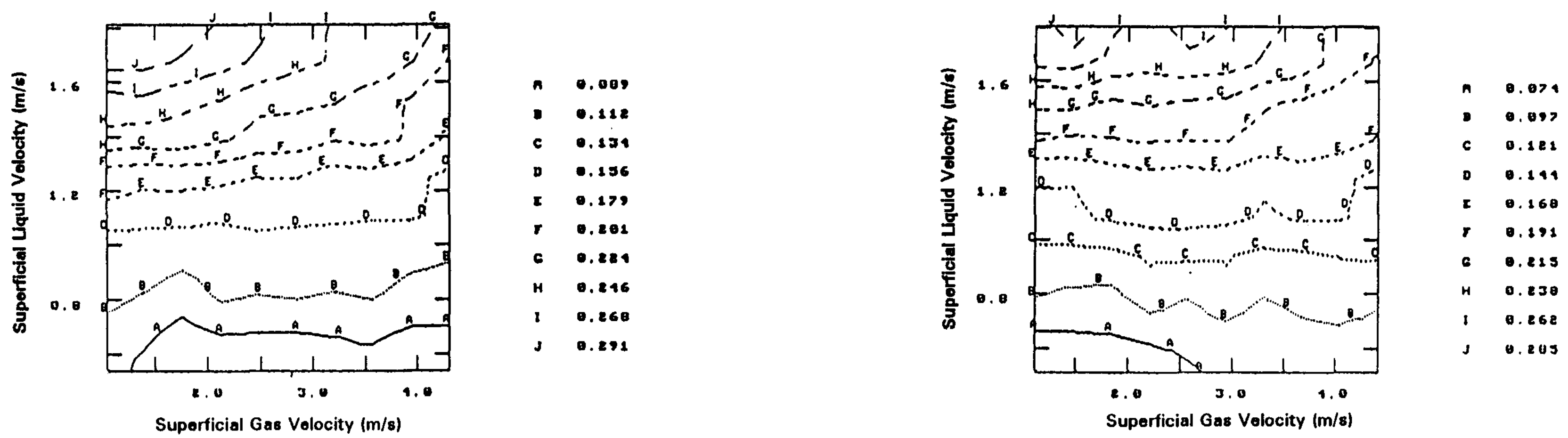
Figure 4. Actual vs. Measured Water-cut (3 Inch Pipeline)



a) at 35% water-cut

b) at 75% water-cut

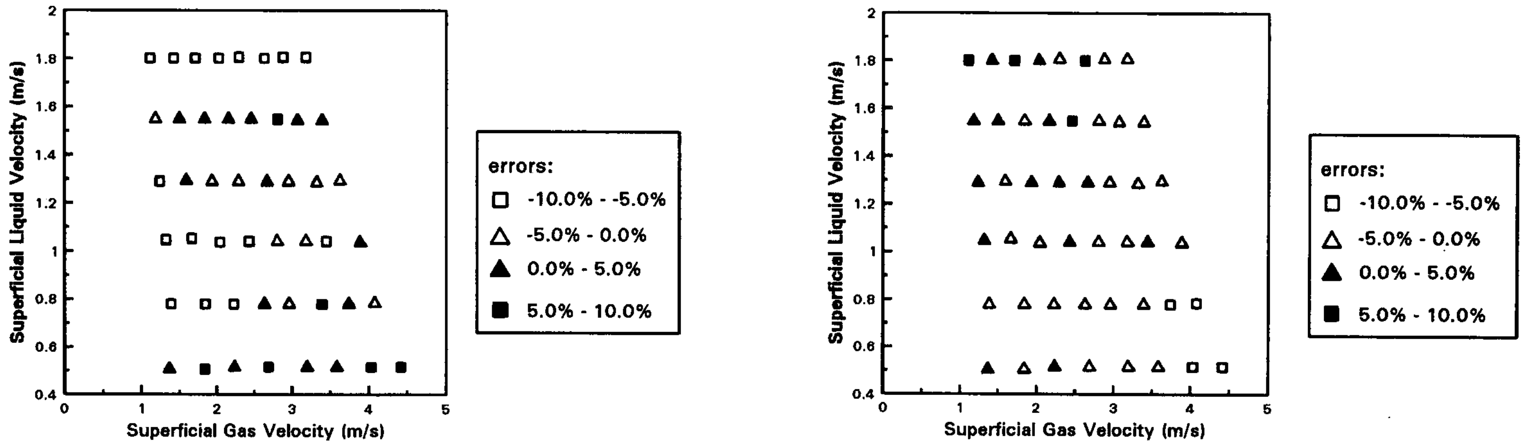
Figure 5. Contour Maps of Sd (t_0 = 0.1S) at 35% and 75% Water-cuts (3 Inch Pipeline)



a) at 35% water-cut

b) at 75% water-cut

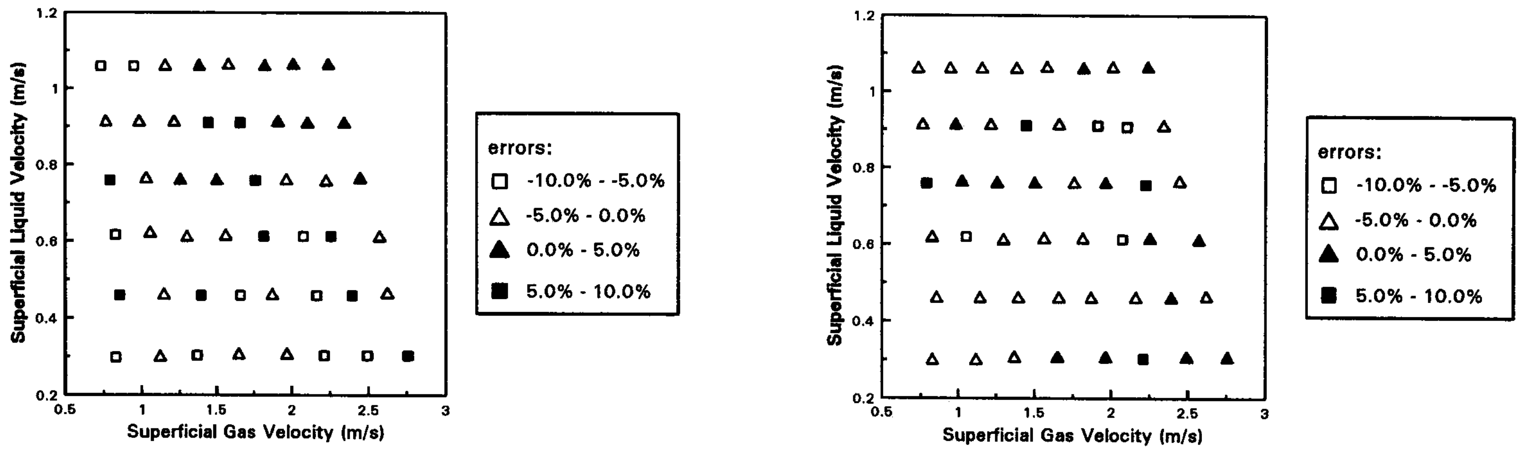
Figure 6. Contour Maps of Tc (C = 5 mbar) at 35% and 75% Water-cuts (3 Inch Pipeline)



a) for liquid

b) for gas

Figure 7. Errors in Liquid and Gas Flowrate Measurement (3 Inch Pipeline)



a) for liquid

b) for gas

Figure 8. Errors in Liquid and Gas Flowrate Measurement (4 Inch Pipeline)