

CRANFIELD UNIVERSITY

ALI AHMED JAMA

**WET GAS FLOW METERING WITH
PATTERN RECOGNITION TECHNIQUES**

SCHOOL OF ENGINEERING

PhD THESIS

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CRANFIELD UNIVERSITY

**DEPARTMENT OF PROCESS AND SYSTEMS
ENGINEERING**

SCHOOL OF ENGINEERING

PhD THESIS

ALI AHMED JAMA

Wet Gas Flow Metering with Pattern Recognition Techniques

Supervisor: Professor M L Sanderson

April 2004

A thesis submitted for the degree of Doctor of Philosophy

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ABSTRACT

The development of many gas condensate fields and the increasing number of marginal fields whose economics do not support conventional bulky separation and processing facilities means that new wet gas flow metering techniques are becoming of greater importance to the oil and gas industry worldwide. For the purpose of this research wet gas flow is defined as multiphase flow (gas-liquid) having in-situ gas volume fraction greater than 95 % at the point of measurement. This research presents a novel wet gas measurement technique involving the use of a standard Venturi meter together with advanced pattern (PR) recognition methods for the detection of liquid presence in wet gas flow conditions and the simultaneous measurement of gas and liquid flow rates without the need for preconditioning of the flow or prior knowledge of either phase. The technique involves four major steps: 1) collection of experimental data spanning the range of flow regimes likely to be encountered in wet gas flow conditions; 2) extraction of flow dependent variables from the Venturi pressure sensors in the form of features; 3) development of PR model for mapping between input features and corresponding gas and liquid flow rates; 4) generalisation test to new and previously unseen flow conditions to determine the accuracy of the Venturi-PR methods developed in this research work.

Data was sampled at 50 Hz using two axial differential pressure sensors and one single-end absolute pressure sensor on a 2-inch horizontally mounted Venturi meter using air-water at normally atmospheric conditions. Extensive features were extracted from the time and frequency domains of the raw data and evaluated for their discriminatory ability between different flow conditions. A Bayesian multi layer perceptron (MLP) neural network was used to construct a non-linear mapping between the different feature vectors and the corresponding gas and liquid flow rates using a correctly labelled training data. When the generalisation performance of different measurement scenarios developed was tested, the cross-sensor data fusion of the amplitude features achieved 100 % of the test data to within ± 5 % error across the whole flow domain of interest. The Venturi-PR results also performed significantly better than published wet gas differential pressure flow correlations over the flow domain of interest.

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Dedicated to my wife Amina

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NOTATION

A	The area of the orifice or Venturi meter upstream area or empirical constant
A_i	Linear prediction coefficient features (e.g. A_1 , A_2 , etc)
A_o	Orifice plate opening area
A_t	The area of the Venturi meter throat
a_i	Neural network output at i th iteration
a_k	k th Linear predictor filter coefficient
AP01	Absolute pressure of the Venturi upstream tapping
B	Empirical constant
BF	Blockage factor
AC	Autocorrelation coefficient
AV	Average value
b_l	l th Linear predictor filter coefficient
b_o	The first term of the transfer function of the linear predictor
C	Empirical constant
C_D	Coefficient of discharge
C_{dg}	Coefficient of discharge of single-phase gas flow
C_{dl}	Coefficient of discharge of single-phase liquid flow
CK	Coefficient of kurtosis
CS	Coefficient of skewness
CV	Coefficient of variation
D	Pipe internal diameter or empirical constant
D_i	Orifice plate inlet pipe diameter
D_o	Orifice plate opening diameter
DP	Differential pressure
DP12	Pressure drop over the Venturi throat
DP13	Pressure drop over the recovery length of the Venturi
d	Venturi throat diameter

E	The velocity of approach factor
E_D	Least mean square error
E_p	Residual error feature of the linear predictor
E_T	Total signal energy
E_w	Sum of squares of the network weights used Bayesian MLP networks
e_n	Linear predictor residual error
E_r	Accuracy error measure
F	Performance function of Bayesian MLP regularisation model
$F(w)$	Forward step of Levenberg-Marquardt training algorithm
f	Multi layer neural network transfer function
f_N	Nyquist frequency
f_s	Sampling frequency
G	Gain factor
H	Hessian matrix
H_z	Linear predictor transfer function
LPC	Linear prediction coefficient
LSF	Line spectral frequency feature (LSF1, LSF2, etc.)
M	The gradient of the best fit line on a Murdock graph
mc	Momentum constant in the steepest descent algorithm
MLP	Multi layer perceptron
N	Total number of points in a sampled record
p	Linear predictor filter order or the number of vectors in a data set
P	Pressure
$P(x)$	Probability density function
$P(z)$	Symmetric polynomial for the direct computation of LSF from LPC
PCA	Principal Component Analysis
Q	Fluid flow rate (gas or liquid)
q_m	Gas or liquid mass flow rate
q_{mg}	Gas mass flow rate
q_{ml}	Liquid mass flow rate

$Q(z)$	Anti-symmetric polynomial for the direct computation of LSF from LPC
R	Correlation coefficient
$r_{xx}(\tau)$	Autocorrelation function
SD	Standard deviation
T	Transpose of a matrix
$TS01$	Temperature of the Venturi upstream tapping
V_{sl}	Superficial liquid velocity
V_{sg}	Superficial Gas Velocity
X	Modified Martinelli parameter
x	Flow quality, the ratio of the gas mass flow to the total mass flow
$x(t)$	Sample time history record
$\bar{x}$	Arithmetic mean
β	Orifice diameter ratio, D_o/D_i or Venturi diameter ratio, d/D
ε	Gas expansibility coefficient
ρ_g	Gas density
ρ_l	Liquid Density
ΔP	Differential pressure
ΔP_l	Differential pressure due to liquid flow
ΔP_g	Differential pressure due to gas flow
ΔP_{tp}	Differential pressure due two-phase (gas-liquid) flow
μ_g	Gas viscosity
μ_l	Liquid viscosity
θ	Empirical constant

CHAPTER 1

INTRODUCTION

Fluid flow from natural gas or gas condensate reservoirs is usually combined with valuable hydrocarbon liquids (e.g. propane, pentane and heavier hydrocarbons) or a binary mixture of hydrocarbon and brine, termed 'wet gas'. Wet gas metering is the commonly used term in oil and gas industry for the metering of multiphase flows where the gas volume fraction (GVF) at actual/measuring conditions is very high ($> 95\%$) when compared to the volume fraction of liquid in the flow stream. Even when single-phase dry gas exist at reservoir conditions, wet gas flow can occur throughout the wellbore as a result of condensation of gas with the reduction of pressure and temperature. Wet gas flows can also occur in the process facilities, where liquid may be formed in a gas stream due to the change in pressure and temperature conditions, or due to liquid carry-over from a separator. Additional liquids also result from the injection of hydrate inhibitors in the flow system.

With the development of many new gas condensate fields around the world and the increasing number of marginal fields whose economics do not support conventional bulky separation and processing facilities, metering the flow in wet gas conditions is becoming of greater importance with several uses of increasing value to the oil and gas operators. For the measurement of wet gas flow the oil and gas industry has identified three key application areas, Couput et al (2000). These are well testing of gas/condensate fields, allocation metering and fiscal metering. Well test refers to the assessment of well performance, which is essential to monitor the production at each well and develop potential new wells. Currently this is mainly done using test separators to separate the phases and then measure separately each phase Beg (1998). However test separators are very costly, heavy and space demanding. Wet gas metering of individual phases without the need for separation can avoid the need for such expensive separation facilities. In allocation metering, the production from one field may be mixed with the production

from another, with the ownership of the two being different. A possible way to economically develop these fields is to transport the unprocessed fluid from different wells over long distances using common pipelines and by sharing facilities with existing gas fields. This is the main driving force behind much of the interest and activities for wet gas metering as it would result in significant cost reduction for marginal fields, potentially allowing wells being metered prior to processing, enabling several fields to share common processing facilities. However, this requires an accurate and cost effective method of measuring the individual well streams prior to commingling and transportation. Fiscal metering is required for commercial and taxation purposes and involves installing high accuracy metering systems to determine quantities and quality of each phase. The measurement accuracy expected for well testing and allocation metering is around $\pm 5\text{-}10\%$ for both gas and liquid phase, while fiscal metering requires measurement with errors less than $\pm 1\%$, Couput et al (2000). Although it is typical to differentiate wet gas from full multiphase flows by considering only two-phase flow (gas-liquid) because of the higher economical value of the gas phase, however when there is an economical value in the recovery of the liquid phase, which may be the case in gas lift operations, then the amount of liquid produced as well as the watercut of the liquid phase is required, demanding three phase flow measurements (gas-oil-water).

The ultimate value of wet gas measurement may therefore be very large in terms of increased and faster reservoir recovery and prevention of disruption to production. Due to these reasons, the requirement to measure wet gas flows is becoming increasingly common in the oil and gas industry worldwide. The characteristic undisturbed flow regime in wet gas flow transport is that of the annular mist flow regime, where the gas phase flows in the centre of the pipe while the denser liquid phase flows as an annular film adjacent to the pipe wall. Depending on the geometry, pressure and flow rates of each phase, significant amounts of the liquid phase may also become entrained in the gas phase and be transported as dispersed droplets. The annular/mist flow regime hence represents a complex measurement problem for standard flow meters. Several methods have so far been evaluated as candidate techniques for application in wet gas flow measurements. One attempt has been to introduce empirical correction constants into the

equations of single-phase gas flow meter, including orifice, Venturi and V-Cone flow meters. A prerequisite of the use of corrective correlations is that the amount of liquid present in the flow stream must be known a priori, which usually requires the incorporation of additional sensors and instrumentation, which increase both the capital and operations costs. Several commercially available multiphase flow meters exist, which have reached advanced technical level and which have shown their potential for measuring the individual flow rates of oil, water and gas. Most of these meters first homogenise the flow in a static mixer or through a blind tee in a vertically upward position in an attempt to meter the pseudo single phase fluid velocity by either a Venturi meter or by cross-correlating two sensors separated by a predefined distance on a straight pipe section and use either gamma densitometers or dielectric sensors to measure the fluid composition. Homogenisation works well for flows, which after homogenisation, the continuous phase is liquid phase, while it is generally found that for flows with gas volume fractions greater than about 90 % to 95 % a homogenised mixture is difficult to create or sustain, Andreussi et al (2000), Fairclough (2000), Falcone et al (2001) and Stewart (2002). Indeed many manufacturers will not quote an expected accuracy beyond 90 % GVF. Further details of the techniques evaluated so far for wet gas flow measurements can be found in chapter 2.

1.1 Research Approach and Methodology

Owing to the increasing importance in the oil and gas industry for an accurate and cost effective method for wet gas metering and the inherent technical limitations of the technologies proposed so far, this research was initiated to investigate an alternative approach to problems of wet gas metering. This research approach was conceived as a follow up from previous works carried out by Darwich (1989), Beg et al (1993), Akartuna (1994), Cai (1995) and Beg (1998), who have validated various methods and instrumentation in conjunction with pattern recognition (PR) techniques for the measurement of liquid continuous multiphase flow rates in horizontal pipelines. The present research aims to extend their approach and evaluate new techniques of pattern recognition methodologies as well as applying these techniques for the first time to wet gas flow measurement.

The principal aim of this research is to develop an advanced signal processing solution, which involves integrating a standard Venturi meter with advanced pattern recognition methods to measure the individual gas and liquid flow rates in wet gas flow conditions without the need for any preconditioning of the flow or prior knowledge of either phase. This will provide an objective pattern recognition technique and develop a novel wet gas metering technique involving a Venturi-PR approach. The key principal approach of this research can be described as follows: -

- Collect an experimental data spanning the full range of flow regimes likely to be encountered in wet gas flow conditions (dry gas, wavy flow, slug flow and annular/mist flow regimes) using air-water flow as the test fluids in controlled laboratory conditions and using a 2-inch horizontally mounted Venturi meter with non-proprietary pressure sensors.
- Extract useful information from the raw data of the Venturi pressure sensors in the form of features (flow dependent variables that can discriminate different flow conditions). Investigate feature trend and discriminatory ability across different

flow conditions and evaluate the effectiveness of feature dimensionality reduction techniques.

- Apply an appropriate pattern recognition model on the basis of their classification accuracy and generalisation ability, when previously unknown flow conditions are introduced. Using the most effective pattern recognition model, evaluate the discriminatory ability of different feature vectors and propose an optimised set of features for the classification of different flow conditions and flow rates using one pressure sensor at a time and different set of feature vectors.
- Investigate the system performance when different feature vectors are fused together as well as the use of cross-sensor data fusion and propose optimised sensors and feature vectors with the best performance across the whole flow domain of interest. Propose a Venturi -PR system comprising optimum features, sensors and pattern classification models that can measure the individual gas and liquid flow rates across different flow regimes (dry gas, wavy flow, slug flow and annular/mist flow regimes).
- Evaluate the effect of flow regime change and operating pressure change on the optimised Venturi-PR system.
- Compare the Venturi-PR results against the published two-phase differential pressure flow correlation as applicable to annular/mist flow regime

1.2 Structure of the Thesis

Chapter 2: This chapter begins with a general overview of regimes encountered in two-phase flow conditions and highlights the flow regimes that characterise annular/mist flow, which is the dominant flow regime in wet gas flow conditions. Current measurement methodologies published for wet gas flow measurements are also reviewed and finally the background information of signal processing, feature extraction and pattern recognition techniques are given.

Chapter 3: Here the experimental rig is discussed including the test section, the Venturi design method, pressure sensors used, the test matrix and the data acquisition system.

Chapter 4: This chapter discusses the procedure developed for feature extraction and selection and feature distribution analysis.

Chapter 5: Flow rate measurement results obtained using Venturi-PR techniques are analysed and discussed here together with the identification of an optimum set of features and pressure sensors for flow rate measurement across the whole flow domain of interest.

Chapter 6: This chapter compares the results obtained from flow rate measurement of Venturi-PR approach against wet gas empirical correlations using only the annular/mist flow regime data.

Chapter 7: The main conclusions of this thesis are summarised here, together with suggestions for future work.

CHAPTER 2

LITERATURE REVIEW

This chapter reviews the current techniques published for the measurement of wet gas flow as well as signal processing and pattern recognition techniques as related to the current research approach and scope of work.

The simultaneous flow of two or three phases of fluid as a multiphase mixture (e.g. gas/liquid) in a single conduit is encountered in many industries, including petroleum, refineries, steam generators, automobile engines, nuclear reactors, paper and pulp industry and many other application areas.

In the oil and gas industry, fluid flow from natural gas or gas condensate reservoirs is usually combined with valuable hydrocarbon liquids (e.g. propane, butane, pentane and heavier hydrocarbons) or a binary mix of hydrocarbon and brine, termed as “wet gas”. Additional liquids also result from the injection of hydrate inhibitors into the flow system. Even when a single-phase gas flow exists at reservoir conditions, wet gas flow can occur through the wellbore and in the production facilities as a result of condensation of gas as pressure and temperature reduce along the wellbore and pipelines.

While there is no universally accepted definition of the range of applicability for the term “wet gas”, there is a general agreement that it is essentially the high gas fraction end of multiphase flow, with small quantities of liquids, typically between 5-10 % by volume. Many researchers have used this range while reporting the results of their wet gas investigations in the open literature. Amongst these we can cite those of Dickinson et al (1993), Roberts (1997), de Leeuw (1997), Lund and Tait (1999), Fincke et al (1999), Andreussi et al (2000), Daniel et al (2000), Steven (2000), Stewart et al (2002), Stewart (2002) and DTI Guidance Notes for Petroleum Measurement, Issue 6 (2002).

2.1 Two-Phase (Gas-Liquid) Flow Regimes

In single-phase flow metering systems, the flow configurations encountered are laminar, turbulent and transitional region between laminar and turbulent. The flow profile is fully developed after few pipe diameters (about 10 to 30) along the pipe length, and hence in general if a meter is designed for a particular single-phase flow configuration, the measurements are usually straight forward. In spite of this, it should be mentioned that at the point of measurement, there could be many problems that can cause the flow meter to deviate from its design specifications (e.g. flow distortion, swirl, pulsation, etc.). Sanderson (1998a) gives a critical assessment of the problems associated with the selection of single-phase flow meters and the performance evaluation techniques.

Single-phase flow measurement techniques cannot be directly applied to multiphase flow, because of the unpredictable and complex behaviour of the latter. The flow regime observed under specific set of flow conditions depends on a number of factors, including flow line geometry (size and shape) and orientation (horizontal, inclined or vertical), flow direction in vertical or inclined flows (up or down). Further complicating the matter is the physical distribution of the phases in the pipe and component transport properties (density, viscosity and surface tension). In a gas-liquid mixture, if there is no heat transfer between the phases, the mass flow rate of each phase will remain substantially constant, but the volumetric flow rates (velocities) will increase progressively as the lower density and viscosity of the gas phase causes it to flow at a higher velocity relative to the liquid phase, a physical characteristic known as slippage.

When multiphase (gas-liquid) flow simultaneously in pipes, the flow regime, pressure and velocity fields are strongly connected. Perhaps the most distinguishing aspect of multiphase flow is the variation in the physical distribution of the phases in the pipe, a characteristic known as flow regime. During multiphase flow in pipes, the flow regime that exists depends on the relative magnitude of the forces that act on the fluid. Gravity, buoyancy, turbulence, inertia, shear and surface tension forces vary significantly with flow rates, pipe diameter, inclination angle, and fluid properties of the phases.

Multiphase phase flow regimes may therefore be viewed as a consequence of the interaction between these forces. To give an indication of the complexity and interaction between the forces mentioned above during multiphase flow in pipes the following description of annular/mist flow, which is the dominant flow regime in wet gas flow conditions is given below.

Annular/mist flow is characterised by a liquid film flowing along the pipe wall, and a gas core containing entrained liquid droplets. The liquid film typically has a wavy surface because of the gas shear forces (otherwise it would have been stratified smooth). In horizontal flow, the film thickness will be maximum at the bottom of the pipe due to gravitational forces. The net transport of liquid in the film is normally small so that the liquid deposited on the liquid film, and droplets are tore off from the film and mixed with the gas. The localised thickness of this annular liquid ring depends on factors such as the liquid and gas flow rates, the density of each phase (which is a measure of buoyancy force), the pipe internal diameter, the viscosity and surface tension of the liquid as these parameters dictate the amount of liquid that will be removed from the film and entrained in the gas. The amount of liquid entrained is determined by such factors as the liquid surface tension as this largely dictates the drop size and therefore the droplet weight and the associated buoyancy force and by the turbulence at the phase interface between the liquid film and the gas core. When drop leaves the liquid film it may become atomised by the drag force of the gas and droplets are being reabsorbed into the annular film.

In vertical upward flow, at some distance from a bend, the film thickness will be radial symmetric and the gas core will propagate with a significant velocity slip to the liquid film. The liquid droplets in the gas core will have a lower velocity than the gas, but significantly higher than the liquid film. Within such a droplet distribution, small droplets will dominate in number, while the larger droplets yield the main contributions to the volume transport. It has been reported that the larger liquid droplets move faster than the smaller droplets due to the complicated turbulence conditions in the gas core, Lopes and Dukler (1986). In annular flow, the drag force exerted on the droplet by the

gas is larger or equal to the gravitational force. Otherwise the liquid droplets would join the liquid film and form a different regime, such as a slug or churn flow.

To accurately calculate the flow in the pipeline all of these relationships would have to be modelled along with the liquid shear at the wall and the liquid/gas shear at the phase interface. It is therefore not surprising that no general analytical model has yet been developed that can accurately predict the flow regime.

This has led to the common practice of characterising multiphase flows with distinct flow regimes. The flow regime must be known for the prediction of pressure gradients in the transportation of oil and gas. A wide variety of these flow regimes have been observed and published in the open literature, including those of Baker (1954), Govier and Aziz (1972), Mandhane et al (1974), Dukler and Taitel (1976). The reason for the variations could be partly due to the subjective nature of these observations and partly from calling the same flow regime by different names.

To simplify matters, sets of main flow regimes are generally agreed upon for two-phase (gas and liquid) flows in horizontal and vertical pipelines as shown in Figures 2.1 and 2.2. These are briefly described below.

2.1.1 Horizontal Flow

The two-phase flow regimes observed in horizontal conduits are often classified into six regimes (Figure 2.1) as follows:

Bubble Flow: Bubble flow consists of discrete bubbles of gas distributed throughout the continuous liquid phase. The bubbles tend to flow in the upper portion of the pipe; however, with higher velocities the cross-sectional distribution tends to be uniform.

Plug Flow: As the liquid flow is reduced bubbles coalesce into larger bubbles or plugs, which flow in the upper portion of the pipe.

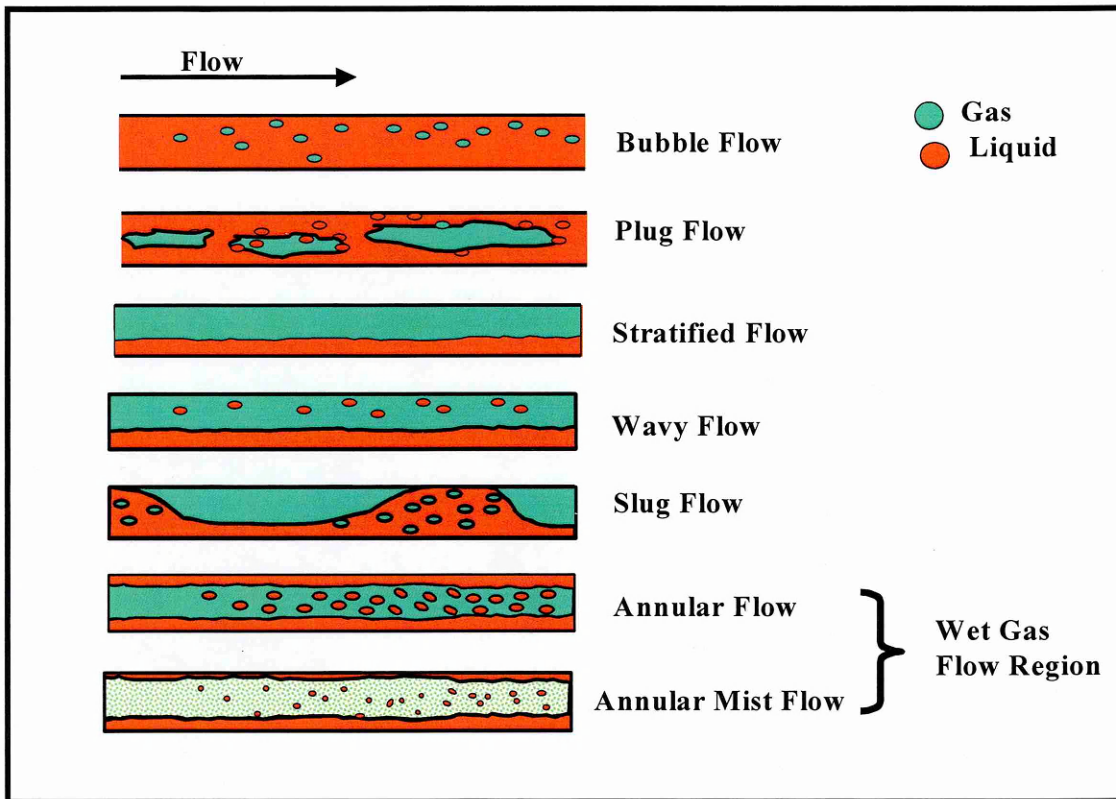
Stratified Flow: If the liquid and gas flow rates are reduced further, a stratified flow regime is set up, in which, the two phases flow separately with a relatively smooth interface, with liquid flowing at the bottom of the pipe due to gravitational forces.

Wavy Flow: As the gas velocity is increased from stratified regime, the increased turbulence causes a more irregular wavy interface to take place, although phases still essentially remain separated.

Slug Flow: Slug flow occurs when the increased liquid flow permits the waves to fill the pipe cross-section, at which stage a high velocity slug of fluid is propagated down the conduit.

Annular/Mist Flow: Annular flow occurs at high gas velocities and is composed of a gas core surrounded by a liquid periphery. The liquid film is usually thicker at the bottom due to gravitational effects, and the interface between the phases is usually wavy allowing entrainment to take place. When significant entrainment occurs, annular flow is described as annular mist. These two flow regimes are commonly associated with wet gas flow.

Figure 2.1: Flow Regimes in Horizontal Pipe



2.1.2 Vertical Flow

Vertical flow regimes (Figure 2.2) are more symmetric than horizontal ones since the gravitational force component acts along the pipe axis. In this case five main flow regimes are defined as shown below.

Bubble Flow: In bubble flow, the gas exists as discrete bubbles interspersed in a continuous liquid medium. The bubbles may also coalesce to form large bubbles or plugs.

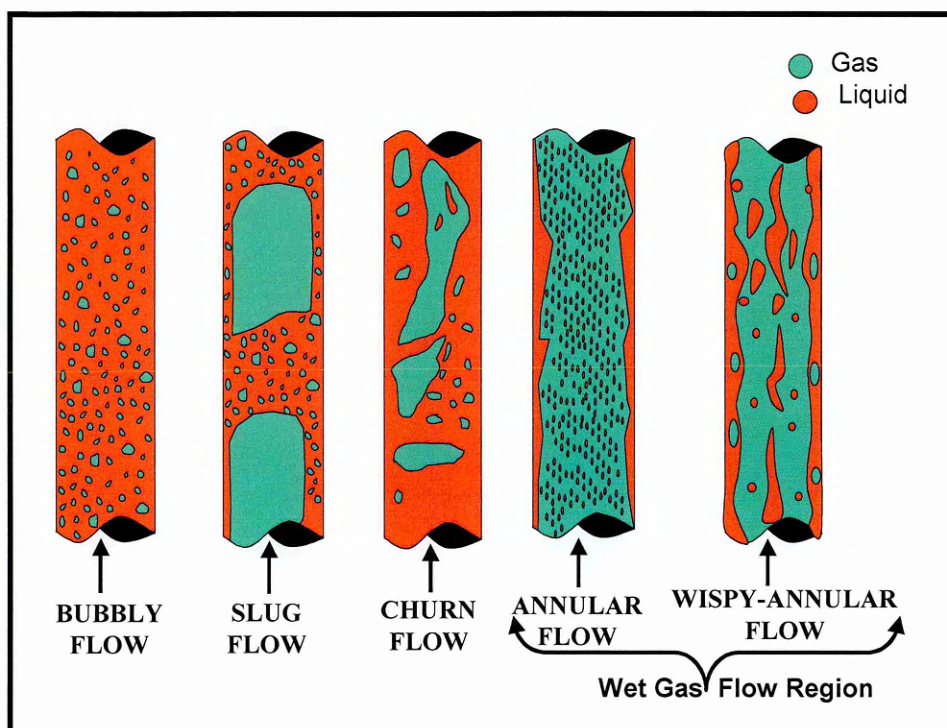
Slug Flow: Slug flow occurs, when the plug diameter approaches the pipe diameter, then the plug of gas forces liquid slugs up the pipe. These slugs may contain entrained gas carried in the wake of the ascending plug.

Churn Flow: As the gas flow is increased, the plugs break up and the flow adopts a random oscillatory nature with the liquid flowing mainly near the pipe wall, but with a large proportion mixing with the gas core.

Annular Flow: In annular flow, the liquid flows as an annular film adjacent to the pipe wall and the gas flows as a core entraining droplets from the wavy interface between the phases.

Wispy-Annular Flow: This flow regime occurs when the gas velocity is high enough to shear a portion of the liquid film from the pipe wall. Most of the liquid tends to flow more as a thick annular film, but it is also entrained into the gas core as large irregular droplets or wisps; the liquid film may also contain entrained gas bubbles.

Figure 2.2: Flow Regimes in Vertical Pipe

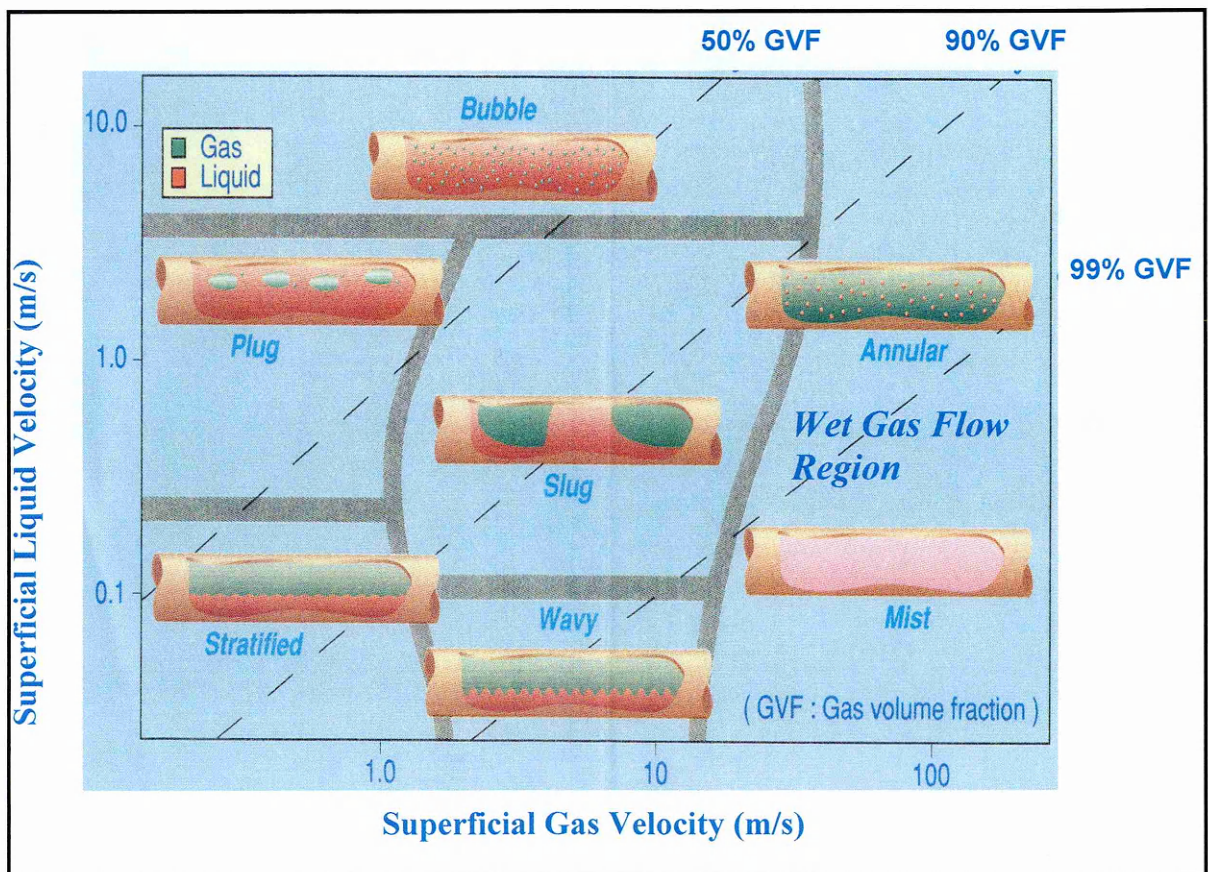


2.2 Flow Regime Maps

The regions over, which the different types of flow can occur are conveniently shown on a “Flow Regime Map” in which a function of the gas flow rate is plotted against a function of the liquid flow rate and boundary lines are drawn to delineate the various regions.

The flow regime map presented by Mandhane et al (1974) for horizontal gas-liquid flow (Figure 2.3) is amongst the most convenient and most widely used flow regime map in industry. However, there are numerous other maps published and are frequently used, and it is left to the end user to make his/her preferred choice as to which map is most convenient to use.

Figure 2.3: Modified Representation of Mandhane et al (1974) Flow Regime Map



2.3 Wet Gas Flow Metering Techniques

Several approaches have so far been evaluated as potential candidate techniques for application in wet gas flow regimes. One attempt has been to use standard dry gas meters and in some cases apply corrections to the measurements based on prior knowledge of how the meter is affected by the presence of liquid in the gas stream. Two-phase (gas-liquid) wet gas flow meters have also been made commercially available, some of which do not require prior knowledge of the liquid phase. Another approach has been to use multiphase flow meters, which measure the gas and liquid flow rates as well as the watercut of the liquid phase. Each of the above techniques will now be reviewed in the following subsections.

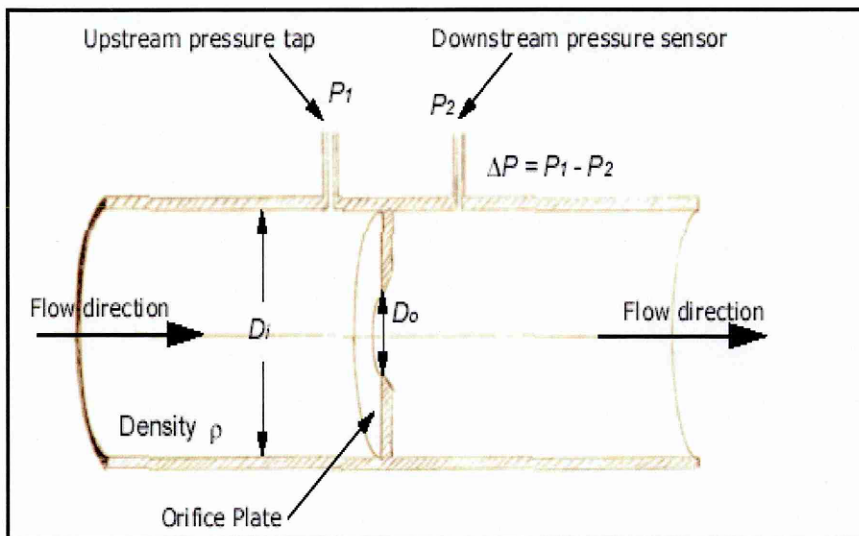
2.3.1 Dry Gas Flow Meters

A number of dry gas flow meters have so far being evaluated for wet gas measurements. These are orifice, Venturi, V-Cone, turbine, vortex, Coriolis and ultrasonic meters. Most of the work with the dry gas flow meters has focussed on evaluating the suitability of differential pressure meters. In wet gas flow conditions the presence of liquid in the gas stream causes the differential pressure over the differential pressure meter to increase (except with orifices, where under-prediction is reported) with respect to the case when only the gas is flowing. This larger differential pressure results in larger calculated flow rate and hence the differential pressure meter is said to over-read. To overcome this, over-reading correction factors have been proposed. A prerequisite of the use of corrective factors is that the amount of liquid present in the flow stream must be known a priori, which usually requires the incorporation of additional sensors and instrumentations. As for the turbine, vortex, Coriolis and ultrasonic flow meters the objective of the work done to date has been to evaluate the effect of the liquids on the meter and quantifying the magnitude and direction of measurement error deviation from dry gas flow conditions. Some progress has been made in solving the physical problems, but no methods for accounting the meter drift or measuring the liquid flow rate have been considered in these developments.

2.3.1.1 Orifice Meters

The orifice meter consists of a flat orifice plate with a circular hole drilled in it (Figure 2.4). There is a pressure tap upstream from the orifice plate and another just downstream. There are three recognized methods of placing the taps (corner tapping, flange tapping and D and D/2 tapping) and the coefficient of the meter will depend upon the position of taps. The orifice meter has a large permanent loss of pressure (73% of the orifice differential) because of the presence of eddies on the downstream side of the orifice-plate. The orifice meter is accepted by industry because of its simplicity in design and reliability in operation, as well as being cheap and easy to install. Hence it is commonly used for the processed and unprocessed flow measurement of natural gas. Many national and international flow metering standards, including BS 1042 and ISO 5167 offer detailed specifications, installation and calculation requirements for orifice and Venturi meters. These standards, however apply only to steady state, single-phase and Newtonian fluid flow.

Figure 2.4: Orifice Flow Meter, taken from Meinold (1984)



The fluid is accelerated by causing it to flow through a constriction, hence the kinetic energy is increased and the pressure energy decreased. The flow rate is obtained by measuring the pressure difference between the inlet of the meter and a point of reduced

pressure as shown in Figure 2.4. The following equation is obtained for the calculation of flow rate.

$$q_m = C_d E \varepsilon A_o \sqrt{2 \rho \Delta P} \quad (2.1)$$

Where C_d is the discharge coefficient, E is the velocity of approach factor $\left(1 / \sqrt{1 - \beta^4}\right)$, β is the diameter ratio, D_o/D_i , ε is the gas expansion factor, A_o is the constriction area, ρ is the upstream density of the flowing fluid, and ΔP is the measured differential pressure between the upstream pressure and the constriction. Note for Venturi β = throat diameter/upstream pipe diameter and $A_o = A_t$, the Venturi throat area.

In two-phase flow situations equation 2.1 would need to be modified in order to take account of the effect of the secondary phase on both pressure and density. In addition, the value of the discharge coefficient is normally known only for single-phase flow conditions and therefore in order to use this value the differential pressure generated by two-phase flow must be converted to what it would be if the mixture were a single phase. In order to make this conversion, the modified Lockhart-Martinelli parameter, X , which is commonly expressed as follows is most often made use of: -

$$X = \sqrt{\frac{\Delta P_l}{\Delta P_g}} = \frac{(1-x)}{x} \left[\frac{\rho_g}{\rho_l} \right]^{1/2} \quad (2.2)$$

A considerable number of papers have been published on the topic of two-phase flow measurements with orifice flow meters. Most of the proposed correlations were derived from different theoretical two-phase flow models and compared with experimental data.

When establishing their correlations, some researchers consider that when a gas-liquid mixture passes through the constriction of an orifice meter mounted in a pipe, it is possible that the device constriction generates a high degree of mixing, and hence they use the homogeneous model to establish their correlation. The homogeneous model

considers the two-phases to flow as single-phase possessing mean fluid properties. In the homogeneous model, the measured two-phase pressure drop is used together with the two-phase homogeneous density, which can be used with the gas mass fraction to derive gas mass flow rates. For the gas phase the following equation can be derived.

$$q_{mg} = \frac{C_d E \varepsilon A_o \sqrt{2 \rho_g \Delta P_{tp}}}{\sqrt{\left[\frac{\rho_g}{\rho_l} + \left[\frac{q_{mg}}{q_{mg} + q_{ml}} \right] \left[1 - \frac{\rho_g}{\rho_l} \right] \right]}} - q_{ml} \quad (2.3)$$

Other researchers consider that because of the curvature effect of the fluid streamline as the flow passes through the constriction; the two-phase mixture might flow separately with the gas velocity not necessarily equal to the liquid velocity, and hence they use a separated flow model when establishing their correlations. However, in reality extensive experimental work showed that the flow at the constriction of a differential pressure two-phase flow meter was neither homogenous nor wholly separated, Lin (1982).

It was found that correlations obtained from the homogeneous flow model or separated model without correction factors are inaccurate. Consequently, more researchers choose a modified homogeneous flow model or a modified separated flow model to form their correlations. These latter correlations contain corrective factors determined experimentally, hence making the purely analytical models to be semi-empirical. The semi-empirical correlations are usually found more accurate, provided they are used within their applicability range.

Murdock (1962) considered the two-phase flow through orifices as separated flow. He correlated the experimental data obtained from different combinations of two-phase fluids, including steam-water, air-water, natural gas-water and natural gas-salt water. The range of his experimental data were as follows:

Pressure, P: 1-63 bar

Quality, x: 0.11-98 %

Orifice diameter: 25.4-31.8 mm

Pipe Inner Diameter: 58.4-101.5 mm

β : 0.26-0.5

Murdock (1962) proposed a method of modifying the single-phase pseudo-gas rate. The resulted equation for the corrected gas flow rate is given below.

$$q_{mg} = \frac{C_{dg} E \varepsilon A_o \sqrt{2 \rho_g \Delta P_{tp}}}{1 + MX} \quad (2.4)$$

Where X is the modified Lockhart-Martinelli parameter and the rest of the symbols have their usual meanings.

A plot of $\sqrt{\frac{\Delta P_{tp}}{\Delta P_g}}$ against $\sqrt{\frac{\Delta P_l}{\Delta P_g}}$ produced a linear equation with a gradient, M and an intercept of 1. Murdock obtained 1.26 for M

Chisholm (1977) also considered two-phase flow through orifices as separated flow, and gave another expression obtained from wet steam measurements with an orifice. The Chisholm's corrected gas mass flow rate is given below.

$$q_{mg} = \frac{C_d E \varepsilon A_o \sqrt{2 \rho_g \Delta P_{tp}}}{\sqrt{1 + CX + X^2}} \quad (2.5)$$

$$\text{Where for } X < 1: C = \left[\frac{\rho_l}{\rho_g} \right]^{1/4} + \left[\frac{\rho_g}{\rho_l} \right]^{1/4} \quad (2.6)$$

Lin (1982) assumed that the gas and liquid phases flow separately through an orifice. He assumed that the discharge coefficient is the same for both phases; the pressure drop for

each phase is the same as the pressure drop for the two-phase flow. After these assumptions, the following equation for the corrected gas mass flow rate was derived.

$$q_{mg} = \frac{C_{dg} E \varepsilon A_o \sqrt{2 \rho_l \Delta P_{tp}}}{\left(\frac{q_{ml}}{q_{mg}} \right) \theta + \sqrt{\frac{\rho_l}{\rho_g}}} \quad (2.7)$$

$$\text{Where } \theta = 1.48625 - 9.26541 \left(\frac{\rho_g}{\rho_l} \right) + 44.6954 \left(\frac{\rho_g}{\rho_l} \right)^2 - 60.6150 \left(\frac{\rho_g}{\rho_l} \right)^3 - 5.12966 \left(\frac{\rho_g}{\rho_l} \right)^4 - 26.5743 \left(\frac{\rho_g}{\rho_l} \right)^5 \quad (2.8)$$

Lin used R-113 (a refrigerant) as the experimental fluid, but he showed that the coefficient θ obtained from the R-113 two-phase mixture could also be applied to wet steam.

Smith and Leang (1975) took a different approach to the problem than the foregoing researchers. They introduced a 'Blockage Factor, F', which is a corrective value applied to the single-phase equation to account for the slow liquid flow partially blocking the fast gas flow. This correlation is for general two-phase flow, but some wet gas data was used. The final equation for the corrected gas mass flow is as follows: -

$$q_{mg} = C_{dg} \varepsilon A_o (BF) \sqrt{2 \rho_g \Delta P_{tp}} \quad (2.9)$$

$$\text{Where } BF = C_1 + C_2 x + \frac{C_3}{x^2} \quad (2.10)$$

and where C_1, C_2 and C_3 are empirical constants found to be equal to 0.637, 0.4211, 0.00183 respectively.

It has been well documented in the open literature that orifice meter measurement errors can occur in liquid/gas flows when using dry gas equations to calculate mass flow rates. Murdock (1962), Chisholm (1977), Mattar et al (1979), Nangea et al (1965) and McBrien (1999a) among others reported that the liquid always increases the differential pressure across an orifice, thus resulting in an over-prediction error if dry-gas equations are used.

In contrast to previous studies, which reported positive meter error with liquid entrainment, investigations conducted by Shen and Ting (1992), Shen et al (1996), Ting and Corpron (1995) and McBrien (1999b) reported that a low liquid to gas mass ratios (up to 3%), orifice meter error was negative. These latter studies indicated that for water/air and unprocessed wet gas flows at moderate pressures, orifice meter readings could become negative if the dry gas orifice equations were used.

Ting and Corpron (1995) experimented with air and water and varied the beta ratio as well as the water to air mass ratio at 41 bar. The greatest error was reported for the 0.7 beta ratio, and the error reached a maximum of -1.7% at the maximum liquid loading.

McBrien (1999a) carried out experiments to evaluate the effect of low water loads on airflow measurements at low pressure (close to atmospheric) and to investigate if observed trends are similar to those already reported for the low water loads at low pressures. Here, a measurable meter shift in predicted flow rate from dry gas conditions was observed for water to air mass ratios ranging from 0.22% to 5.9% . All observed errors were positive with some reaching a maximum and then decreasing as water to air ratio was increased to greater values.

McBrien (1999b) investigated the effects of low liquid (ethylene glycol) loads on the orifice metering of high pressure (46 to 50 bar) with three different beta ratios (0.31, 0.6 and 0.69). The greatest positive shifts (up to 1.4%) occurred for the larger values of liquid/gas mass ratio ($>2\%$) and at the lower values of beta. For liquid/gas mass ratio less than 2% and beta ratio of 0.6 and 0.69, the meter shift was initially negative (as low as -0.7%). These findings are in closer agreement with those of Ting and Corpron (1995).

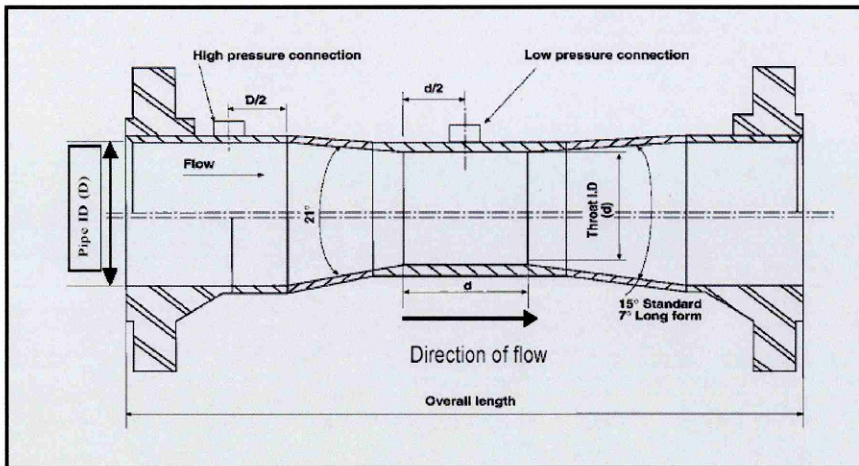
The reasons for the observed shifts have been speculated to be due to flow profile change through the meter as a result of phase change (water evaporation due to temperature variations), but at this stage more research is needed to confirm as to what sort of flow profile is occurring through the meter and what exactly is causing the meter to under-predict the gas flow rate at low liquid loadings.

An observed effect of orifice meters, when applied to wet gas flow is the hold up of liquid before or after the plate. As the velocity increases, the amount of liquid held before the plate is minimal. The low-pressure re-circulating region after the plate however can hold a significant amount of liquid. In addition the orifice plate meter also induces the highest-pressure loss in comparison with other differential pressure meters and hence this meter is not currently considered for future wet gas metering developments.

2.3.1.2 Venturi Meters

The attraction of this meter (Figure 2.5) lies in its high-energy recovery so that it may be used where only a small pressure head is available, though its construction may be more expensive than orifice plates. To make the pressure recovery large, the angle of downstream cone is small so boundary layer separation is prevented and friction losses minimised. Since separation does not occur in a contracting cross section, the upstream cone can be made shorter than the downstream cone with but little friction, and space and material are thereby conserved. In wet gas flow conditions; the presence of liquid in the gas stream causes the differential pressure over the differential pressure meter to increase with respect to the case when only the gas is flowing. This larger differential pressure results in larger calculated flow rate, and hence the Venturi meter is said to over-read. The differential pressure flow meter calibrated in dry gas flow would of course read this increase as additional gas flow rate.

Figure 2.5: Venturi Meter, taken from Stewart (2002)



Dickson et al (1993) used Venturi meters in gas/condensate producing wells in the Southern North Sea. They confirmed Venturi meters measuring natural gas around 80 bar and with liquid fractions up to 4 % by volume had over-estimated the actual gas mass flow rate, and this over-estimation could be corrected using empirical correlations of Murdock (1962) and Chisholm (1974). For liquid fractions of up to 4 %, the Venturi over-reading appeared to linearly increase as the liquid content increased. They proposed a modified Murdock equation by substituting the Murdock constant (1.26) with a Venturi constant under field conditions.

De Leeuw (1997) developed a new expression for use with Venturi meters in wet gas conditions from analysis of experimental data collected in large-scale multiphase flow facility, located near Trondheim, Norway. The test envelope covered the majority of wet gas operating conditions, which can be encountered in the field. The pressure was varied between 15 and 95 bar. All tests were performed with diesel oil as the liquid and nitrogen as the gas phase, with GVF varying between 0.9 and 1. A horizontally installed 4-inch Venturi meter with a throat diameter of 39 mm, resulting in a β ratio of 0.401 was used. Differential pressures were measured over the throat of the Venturi, for the flow rate calculations and also across the meter to measure the overall pressure loss of the Venturi tube.

De Leeuw's correlation is based on the original Chisholm's correlation for orifices, with the only difference being that the over-reading depends on the actual gas velocity or Froude number and operating pressure. He showed that this new correlation accounts for the over-prediction experienced by Venturi meters in wet gas better than those developed for orifice meters by Murdock (1962) and Chisholm (1977). The equation for the corrected gas mass flow rate is given below.

$$q_{mg} = \frac{C_d E \varepsilon A_t \sqrt{2 \rho_g \Delta P_{tp}}}{\sqrt{1 + CX + X^2}} \quad (2.11)$$

$$\text{Where } C = \left(\frac{\rho_l}{\rho_g} \right)^n + \left(\frac{\rho_g}{\rho_l} \right)^n \quad (2.12)$$

and where $n = 0.606(1 - e^{-0.746 Fr_g})$ for $Fr_g \geq 1.5$, i.e. an annular mist flow regime
and for stratified flow regime, $n = 0.41$ for $0.5 \leq Fr_g \leq 1.5$

Comparing equation (2.11) with Chisholm's equation (2.5) shows that they are identical, however equation 2.12 replaces Chisholm's equation (2.6), transforming the equation to a function of pressure and gas flow rate. The data used by de Leeuw were a Venturi meter wet gas field data set and a test centre data set, using diesel oil and nitrogen.

Steven (2001a) used a standard Venturi meter supplied by ISA Controls Ltd with a β ratio of 0.55 on the wet gas horizontal flow loop of the National Engineering Laboratory (NEL), Glasgow, UK. The upstream pipe diameter was 5.5-inch and the throat diameter was 3-inch. Testing was done at pressures of 20, 40 and 60 bar with test fluids being nitrogen and kerosene and the GVF ranging from 95 % to 100 %. Steven's results confirmed de Leeuw's findings that the Venturi over-reading was dependent on the gas Froude number and the pipeline pressure, and presented a new empirical correlation based on his own data. Steven compared the performance of previous two-phase flow correlations against his newly developed correlation and concluded that the newly developed correlation produced performed better than previous correlations. This

correlation was later updated by Steven (2001b) and further modified and updated by Steward et al (2002).

The corrected gas mass flow rate is given below as reported by Steward et al (2002)

$$q_{mg} = \frac{C_d E \varepsilon A_t \sqrt{2 \rho_g \Delta P_{tp}}}{\left(\frac{1 + AX + B Fr_g}{1 + CX + D Fr_g} \right)} \quad (2.13)$$

$$A = 2.085 + \left[0.0060 / \left(\frac{\rho_g}{\rho_l} \right)^2 \right] \quad (2.14)$$

$$B = -0.08 + \left[0.0001 / \left(\frac{\rho_g}{\rho_l} \right)^2 \right] \quad (2.15)$$

$$C = 0.548 + \left[0.0042 / \left(\frac{\rho_g}{\rho_l} \right)^2 \right] \quad (2.16)$$

$$D = -0.079 + \left[0.00009 / \left(\frac{\rho_g}{\rho_l} \right)^2 \right] \quad (2.17)$$

The limits of Steven's correlation is for pressure $20 \text{ bar} < P < 60 \text{ bar}$ and gas flow rate of $400 \text{ m}^3/\text{h} < Q_g < 1000 \text{ m}^3/\text{h}$.

The National Engineering Laboratory (NEL) in Glasgow, UK have recently carried a project, which looked at the performance of some of standard dry gas meters in wet gas flow conditions. This was done as part of the 1999-2002 Flow Measurement Programme, sponsored by the UK's Department of Trade and Industry (DTI). Stewart (2002)

compiled and reported the results of this work. The meters tested included Venturi meter (with different β ratio), V-Cone, turbine, vortex and Coriolis meters.

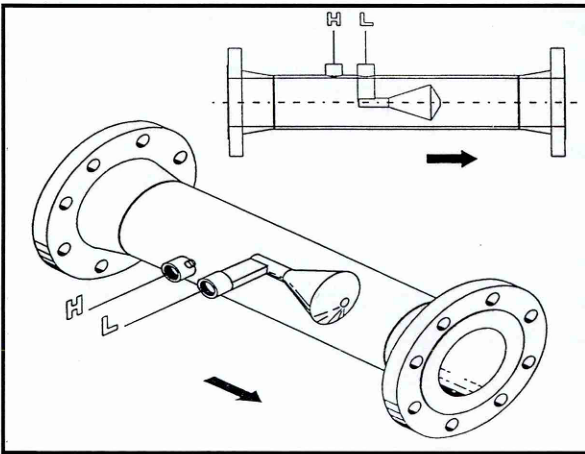
Three 100 mm standard Venturi meters were tested in the horizontal wet gas flow loop at the NEL as part of the above mentioned work. The meters, with β values of 0.4, 0.6 and 0.75 have been tested at 15, 30 and 60 barg across a range of gas and liquid flow rates. The test fluids were nitrogen and kerosene. Each Venturi meter was calibrated in dry gas at each test pressure prior to the respective wet gas tests, and results confirmed that Venturi meters over-predict the gas mass flow rate, compared with what had been the measured without any liquid presence. The study also used the Venturi wet gas correlations of de Leeuw (1997) and Steven (2001a) to correct the over-reading and showed that both correlations only fitted well with some part of the data. The study concluded that further work was required to expand or develop new correlations that were based on a wider database and varying parameters (e.g. taking into account β value effect).

Falcone et al (2003) reported an on going research project at the Imperial College, London for the development of a new wet gas measurement technique known as ANUMET. The concept behind the ANUMET system is that of deducing the liquid flow rate from measurements on annular flow in a vertically upward straight pipe section and then using this liquid flow rate in the interpretation of the pressure drop data from a Venturi placed downstream of the straight pipe section in order to deduce the gas flow rate. The liquid flow rate is determined by measuring the liquid film thickness and the pressure gradient along the straight pipe section by using gamma densitometry and conductance probes and differential pressure transducer. A homogenised density model is then used to calculate the gas mass flow through the Venturi. Preliminary results showed that the accuracy in liquid flow rate estimation is worse than $\pm 20\%$ and that the main limitations of this concept relate to the instrumentation chosen for the liquid film thickness measurements, namely the gamma densitometer. Other alternative techniques were suggested for the liquid film measurement such as ultrasonic and fluorescence.

2.3.1.3 V-Cone Flow Meters

McCrometer Inc. introduced the V-Cone flow meter in 1986. As with other differential pressure devices, the flow constricts to create high and low velocity areas, which creates a differential pressure signal. However, the V-Cone's constriction is not a concentric opening through the centre of the pipe, like the orifice. The V-Cone creates an annular opening, forcing the fluid to flow around a cone suspended in the centre of the pipe as shown in Figure 2.6 below. Equations for the V-Cone are same as those for orifice and Venturi meters, except that the V-Cone β is the ratio between the square root of the open area in the pipe and the square root of the open area at the meters constriction. In wet gas flow, any liquid volume along the pipe would pass through without touching the cone. The V-Cone is therefore suited to wet gas applications.

Figure 2.6: V-Cone Flow meter, taken from Ifft (1997)



The most significant of the limited work carried using V-Cone flow meters operating in wet gas are those of Stewart (2002) and Stewart et al (2002) who carried out tests on the performance of the V-Cone at 15, 30 and 60 bar line pressures. The results showed that the meter over-read the gas mass flow rate when exposed to wet gas flows. The general trend of the over-reading was similar to that of Venturi meters, but with a smaller magnitude. The correlations of de Leeuw (1997) and Steven (2001) were also used to account for the over-predictions. The maximum measurement error achieved with de Leeuw correlation for all pressures and for $\beta=0.75$ was -23.1% , while this error was

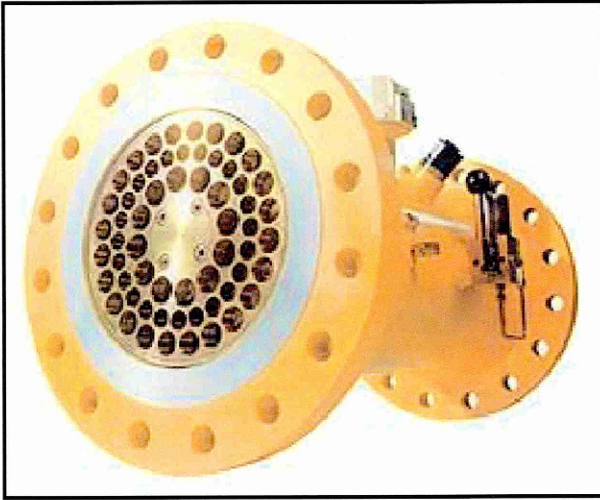
reduced -17.6% for $\beta=0.55$. The errors obtained with the use of the Steven's correlation were -9.6 and -8.1% for the same two cases respectively.

All the efforts so far has been to study the effect of liquids have on the dry gas calibrated V-Cone flow meters with no dedicated work carried out yet to develop special correlation to account for the over-reading for V-Cone flow meters, nor has there been any attempt made to measure the liquid rate. Nevertheless, the V-Cone meters are, like the Venturi meters physically well suited to wet gas flow conditions, as they are not affected by liquid pooling experienced by orifice and have lower pressure drop. V-Cone flow meters also give a lower over-reading than Venturi meters in wet gas flow conditions.

2.3.1.4 Turbine Flow Meters

Turbine flow meters (Figure 2.7) measure the volumetric flow of the flowing fluid (liquid or gas). The unit consists of a multiple-bladed rotor, housed in a non-magnetic body mounted with a pipe, perpendicular to the liquid flow. The rotor spins as the fluid passes through the blades. The rotational speed is a direct function of flow rate and can be sensed by magnetic pick-up, photoelectric cell, or gears. These instruments operate linearly with respect to the volume flow rate. Because there is no square-root relationship (as with differential pressure devices), their rangeability is greater. Baker (1998) gives an extensive coverage of the considerable range of turbine designs together with a review of their principle operations.

Figure 2.7: Turbine Flow Meter, taken from Stewart (2002)



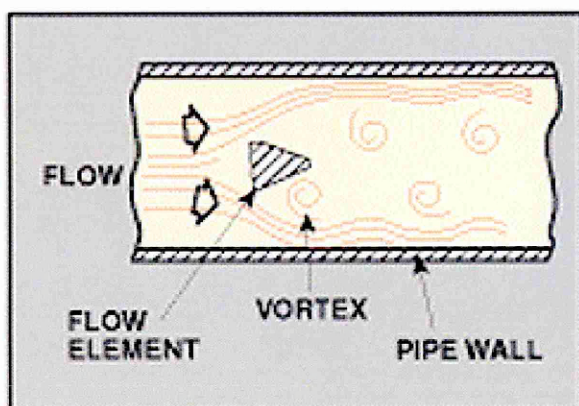
The only work cited to evaluate the performance of turbine meters in wet gas was that of Stewart (2002), who described a series of wet gas tests on a 6-inch Instromet gas turbine meter at the NEL (as part of the DTI sponsored project mentioned above). The presence of even small quantities of liquid produced a significant effect on turbine meter readings at Reynolds numbers below 5×10^6 . At higher Reynolds numbers the liquid appeared to have little effect on the meter. The author concluded that additional testing, preferably on more than one model of turbine meter would be required to allow a better examination of turbine meters in wet gas conditions.

It may be stated that due to the potential damage to the blades caused by liquid impacting on them, turbine meters are not suitable candidates as wet gas flow meters. However as they are normally used for custody transfer metering of processed natural gas flows, there may be situations where for example due to unanticipated pressure drop in the pipeline, free liquid may be formed or as a result of insufficient production separators, liquids may be carried over to a supposedly dry gas metering leg, where the turbine could be exposed to a wet gas conditions. In these situations, more research would be helpful; both to verify the meter shift and to better design the meters so that they can physically tolerate small liquid entrainments.

2.3.1.5 Vortex Flow Meters

Vortex meters make use of a natural phenomenon that occurs when a liquid flows around a bluff object. Eddies or vortices are shed alternately downstream of the object. The frequency of the vortex shedding is directly proportional to the velocity of the liquid flowing through the meter, Figure 2.8. The three major components of the flow meter are a bluff body strut-mounted across the flow meter bore, a sensor to detect the presence of the vortex and to generate an electrical impulse, and a signal amplification and conditioning transmitter whose output is proportional to the flow rate. Sanderson (1998b) gives a review of vortex shedding flow meters, together with other members of this class including the Swirlmeter, Coanda type meters and mechanical oscillators.

Figure 2.8: Vortex Flow Meter, taken from Meinold (1984)



Vortex meters are normally used for processed natural gas and steam flow. A typical quoted accuracy in these applications for uncalibrated meter is of the order of $\pm 1.5\%$ of reading and $\pm 1.25\%$ for calibrated flows, Sanderson (1998b).

Agar Corporation have recently commercialised a new wet gas meter (WGM), utilising a vortex meter in conjunction with dual Venturi meters, Agar (2002). According to Agar (2002), the WGM utilises the vortex meter for the measurement of the total volumetric flow rate (presumably assuming a homogeneous flow through the meter), and dual Venturi meters for the liquid/gas determination. It was mentioned that during laboratory

tests, which covered a GVF of 50 to 100 %, the vortex meter readings started to be affected by the liquid loading in the flow stream as the GVF reduced below 50 %. Under these conditions only the dual Venturi meters were used for both volumetric flow rates and GVF. However no accuracy figures were quoted from the laboratory testing. Further tests were conducted at an offshore field in the Gulf of Mexico to measure the amount of wet gas being received at the pipeline hub. The wet gas was measured by the WGM and compared to the dehydrated gas measured by an orifice meter on the production platform, and the two meters produced an agreement of better than ± 5 %.

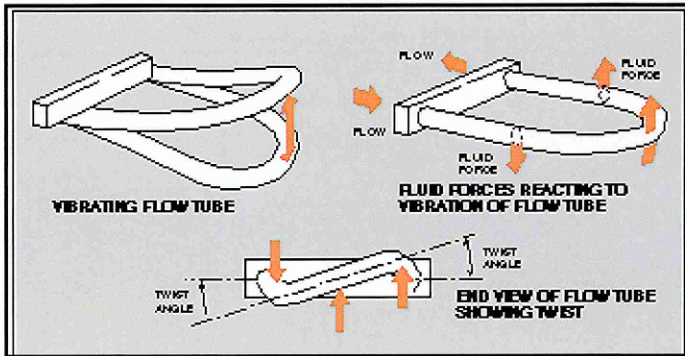
A 4-inch Fisher-Rosemount vortex meter was tested by the NEL in a horizontal orientation in wet gas at 15, 30 and 60 barg, Stewart (2002). The results showed that the meter over-estimated the reference gas flow rates with a relative error ranging from 0 to 30 %, which was dependent on liquid volume fraction and gas velocity. The apparent gas flow rate measured by the meter increased with increasing liquid volume fraction, causing an over-estimation of the actual gas flow rates, while as the pressure increased the meter error decreased due to a reduction in the hold up of liquid (reducing the slip). It mentioned that the meter behaviour was independent of the superficial gas velocity for the majority of the tested liquid volume fractions. These results indicated that if vortex meters are used for unprocessed natural gas, large measurement errors can be expected as the presence liquid causes the meter to over-estimate the actual gas flow rates.

2.3.1.6 Coriolis Flow Meters

Coriolis meters (Figure 2.9) are true mass meters that measure the mass rate of flow directly as opposed to volumetric flow. Coriolis meters are available in various designs. A popular unit consists of a U-shaped flow tube enclosed in a sensor housing connected to an electronics unit. Inside the sensor housing, the U-shaped flow tube is vibrated at its natural frequency by a magnetic device located at the bend of the tube. This action causes the vibrating tube to twist. The amount of twist is directly proportional to the mass

flow rate of the fluid flowing through the tube. Stansfeld (1998) gives an introduction to the different designs of Coriolis meters available.

Figure 2.9: Coriolis Flow Meter, taken from Meinold (1984)



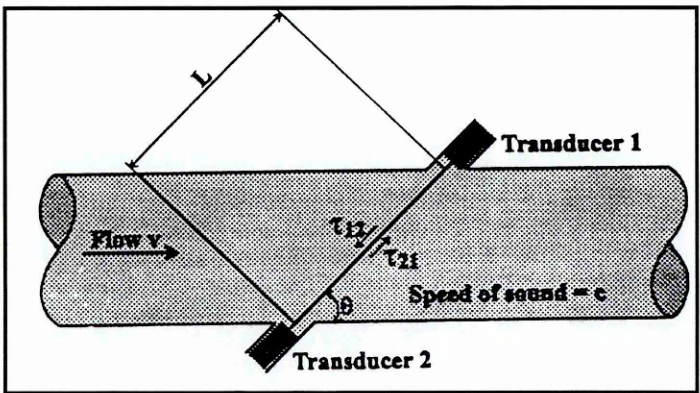
Although Coriolis meters are traditionally used for liquid flow measurements, most manufacturers now offer them for gas applications. They calibrate the meter in water and use that calibration for gas flow as well. Due to their ability to directly measure the mass flow rate; there is a particular interest to evaluate Coriolis performance in wet gas flow conditions. The results showed that the Coriolis meter showed a clear pressure dependency in dry gas conditions, with the error becoming increasingly negative with increasing pressure. The meter also exhibited even greater errors in wet gas flow conditions. At all liquid fractions tested, the meter under-predicted the reference gas mass flow rate with measurement errors reaching as high as 50 % in higher liquid loading.

The above results showed that the Coriolis meter under-predicted the actual gas density in both dry and wet conditions, leading to the meter under-estimating the gas mass flow rate. According to previous research work on general two-phase flow, Wood (2002), the meter can function up to 10 % gas entrainment provided the two-phase gas-liquid flow remains homogenised within the small vibrating tubes of the Coriolis meter. However, as the gas comes out of solution then the meter will stall, as the gas will affect the coupling between the fluid and the vibrating tube making it difficult for the meter sensor to determine a resonant frequency.

2.3.1.7 Ultrasonic Flow Meters

There are many types of ultrasonic flow meters, namely the time of flight, also known as transit time (Figure 2.10, taken from unpublished work of BHR Group Limited), the Doppler shift method and cross-correlation techniques. Sanderson (1998c) gave a review of the ultrasonic flow meters in general and their performance in single-phase flow measurements. Amongst these different ultrasonic flow meters, the time of flight is the method that has been particularly applied and further developed for the measurement of gas flow. It is this method with its multi-path configuration that has now gained acceptance for the measurement of natural gas flow.

Figure 2.10: Ultrasonic time of flight set up



This method is based on the primary measurement of distance and time, and is independent of the velocity of sound, provided that the velocity of sound is constant during the flight in both directions. However, unlike differential pressure flow meters, there are as yet no correction methods established to account for the over-reading. The objective to date has therefore been to measure the gas flow rate, preferably unaffected by any liquid presence. Nevertheless, this has not been a success as the liquid accumulates in the transducer ports and thereby severely affects their accuracy.

Zanker et al (1994) investigated the moisture effect on the transducer ports in a horizontal pipe. They noticed that the moisture collects in the transducer ports, short circuits the

acoustic isolation between transducer and body, bridges the small clearance between port and transducer and contaminates the transducer front face. They mentioned that at velocities less than 5 m/s, the two-phase flow was stratified, creating a liquid film running in the bottom of the pipe. Under these conditions, it was found that 1% liquid by volume made the ultrasonic meter read about 4-5 % high and as a result of this liquid film, one of the transducers at the bottom of the pipe failed.

Karnik et al (1997) tested an 8-inch multi-path ultrasonic flow meter with injection of controlled liquids of up to 5 % by mass. Similarly, they also observed that, once the meter was flooded with liquid, some of the ultrasonic paths were unable to recover without manual intervention. These investigations revealed that the liquid mainly collected within the lower transducer ports.

Stobie et al (1998) carried out modifications on a four path ultrasonic flow meter on behalf of British Gas Group. The original meter was designed for clean dry sales gas. It was noticed that the practical feature of the design in wet gas was because of the small clearance between the transducer (1 1/8-inch diameter) and port (1 1/4- inch diameter). Liquids can very easily bridge this 1/16-inch radial clearance, cause acoustic coupling to the steel meter body and create noise to appear in the received signals.

Owing to the large errors obtained with liquid presence and the practical problems with liquid accumulation in the transducer ports, it is currently recommended that ultrasonic flow meters should not be used in wet gas flow conditions, where the liquid volume fraction (LVF) is greater than 0.5 %, and ideally these meters should not be installed in flow lines prior to separation other than for testing or comparison purposes, DTI Guidance Notes for Petroleum Measurement, Issue 6 (2002).

2.3.1.8 Derivation of Liquid Flow Rate

As the above literature and discussions highlighted, most of the current and planned future work on the development of wet gas measurement techniques are driven towards differential pressure meters, with the Venturi meter receiving most attention due its long history in the industry and because of its suitability to wet gas flow measurements. Among the over-reading correlations published for Venturi meters so far, the method most applicable to wet gas Venturi flow meters is that derived by de Leeuw (1997) as his work focussed especially on Venturi meters operating in wet gas field conditions. However in order to use this correlation the liquid flow rate must be known a priori. An off-line technique involving the use of tracer dilution, which was first introduced by de Leeuw (1994) is recommended for this purpose, DTI Guidance Notes for Petroleum Measurement, Issue 6 (2002). In the tracer dilution technique a chemical compound with measurable characteristics, such as fluorescence is injected into flow stream at known concentrations and at a controlled rate, where it mixes with and is diluted by the liquid phase of the flow stream. Samples of the liquid phase of the flow stream are collected and the fluorescence of the tracer in the samples is measured to calculate the concentration of the tracer. The liquid phase flow rate in the flow stream can then be calculated as follows:

$$Q_{liquid} = \frac{C_{tracer}}{C_{liquid}} * Q_{tracer} \quad (2.18)$$

Where C is the tracer concentration and Q is the tracer flow rate.

Where more than one liquid phase exist, specific tracers must be selected with a preferential affinity for each liquid phase. One major drawback of the tracer dilution technique is that it does not provide a continuous and an online indication of the liquid flow rate and it requires repeat tests whenever a change in the liquid rate is perceived. This technique requires 150D between the injection point and sampling point to ensure complete mixing. The dye should be injected into the top of the pipe and the sample

extracted from the bottom. The injection flow rate must also be significantly smaller than the liquid flow rate (but in wet gas situations this may not be the case), Wood (2002). The liquid composition can also be determined using compositional PVT analysis, which involves taking representative sample of the hydrocarbon composition at a particular temperature and pressure and then carrying out flash calculations using Equations of State (EoS) to determine the condensate and gas fractions. Other techniques include gamma densitometers and dielectric sensors.

2.3.2 Commercial Wet Gas Flow Meters

There are number of commercial meters available for wet gas flow measurement in the market. These meters can be subdivided into two main categories, those that provide two-phase (gas and liquid) flow measurements, commonly referred to as wet gas flow meters and those that measure the gas and liquid flow rates as well as the watercut of the liquid phase referred to as multiphase flow meters. Each of these categories will now briefly be described below.

2.3.2.1 Wet Gas Flow Meters

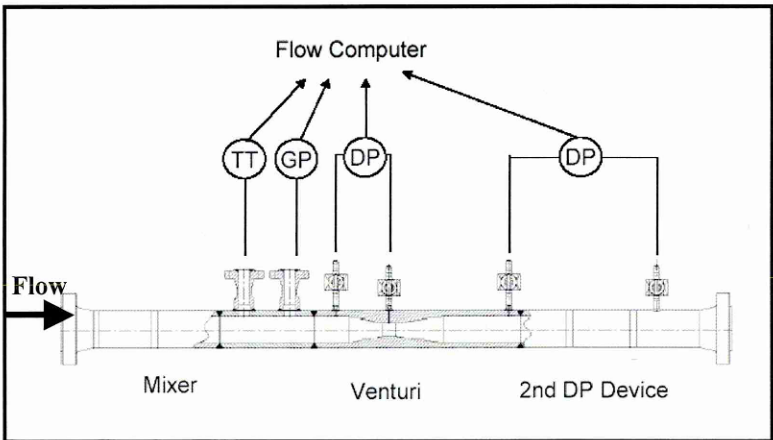
Table 2.1 below summarises commercially available two-phase (gas-liquid) wet gas meters. It must be noted that the uncertainties quoted, are the vendor claims and specification without third partly verifications, and they refer mainly to laboratory tests conducted under controlled conditions. Furthermore it is not clear from the literature cited if the quoted uncertainties are absolute or relative errors. According to Couput et al (2000), the expected accuracy from wet gas flow meters are $\pm 10\%$ for both gas and liquid phases and $\pm 5\%$ for allocation purposes. Figures around 20% or more could be acceptable for flow assurance. Fiscal metering requires accuracies of better than $\pm 1\%$.

Table 2.1: Commercial Wet Gas Flow Meters Adapted from Mehdizadeh (2003)

Metering System	System Designation, Vendor	Volumetric Uncertainty Vendor Spec.	
		Gas	Liquid
Dual Venturi	Dualstream, ISA-Solarton	$\pm 5\%$	$\pm 10\%$
Dual Venturi with Vortex	WGM, Agar	$\pm 5\%$	$\pm 5\%$
Extended Venturi	OneStep, FMC	$\pm 2\%$; GVF < 95 %	$\pm 6\%$
Orifice with isokinetic sampling	VEGA, TEA	$\pm 3\%$	$\pm 3\%$
Venturi with tracer system	SmartVent, Petrotech	± 2	$\pm 15\%$
V-cone/Venturi, Microwave	WGM, Roxar	$\pm 3-5\%$	$\pm 3-5\%$

Dualstream Wet Gas Flow Meter: This meter is based on technology developed by Advantica Technologies (formerly the R & D division of British Gas PLC) and further commercialised by ISA-Solarton. This meter (see Figure 2.11) uses two differential pressure devices in series and works on the principal that the two differential pressure devices have different over-reading characteristics, and at the same conditions and flow rates, one will exhibit a higher over-reading than the other. Two Murdock type simultaneous equations are formed which can be solved to yield the gas and liquid flow rates. Laboratory measurements showed an accuracy of $\pm 4\%$ FSD for the gas flow rate and $\pm 6\%$ FSD for the liquid rate, Lund et al (1999), Daniel et al (2000). The key to this approach is that there must be sufficient difference in the over-readings to allow discriminations between the meters. A version that uses tracer dilution technique for the liquid flow rate measurement is also said to be available, Wood (2002).

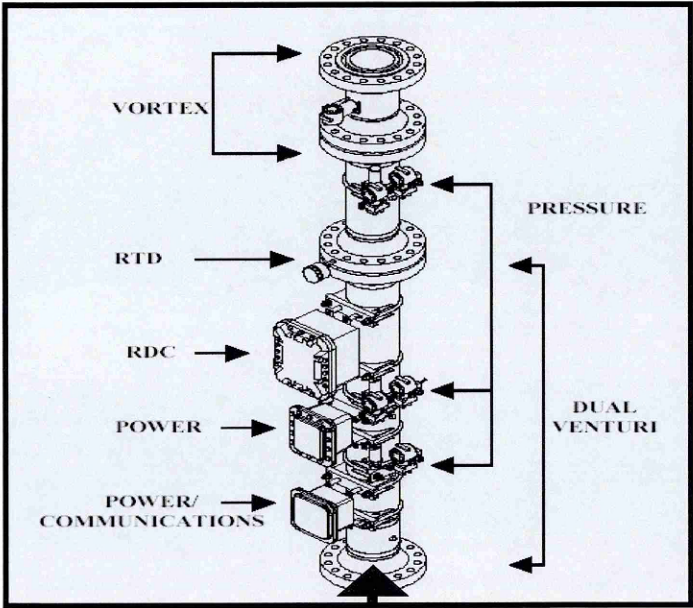
Figure 2.11: Dualstream Wet Gas Flow Meter, taken from Webb (2003)



Dual Venturi with Vortex (WGM): This is a new wet gas meter in the market and is developed by Agar Corporation, Agar (2002). As shown in figure 2.12, the WGM uses three independent flow meters: Volumetric (Vortex) and two Momentum flow meters (Ventures) to solve the basic Momentum and Energy Conservation equations. As well as trials at two test flow loops; WGM was installed and field-tested in the Gulf of Mexico. When the WGM's data on the receiving platform was compared to the orifice meter's

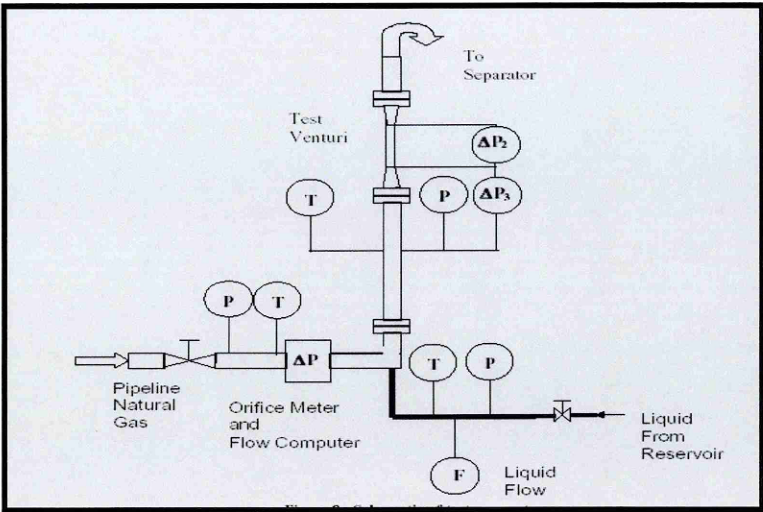
readings for dehydrated gas shipped on the production platform, the measured gas volumes were said to be better than $\pm 5 \%$.

Figure 2.12: Dual Venturi with Vortex WGM, taken from Agar (2002)



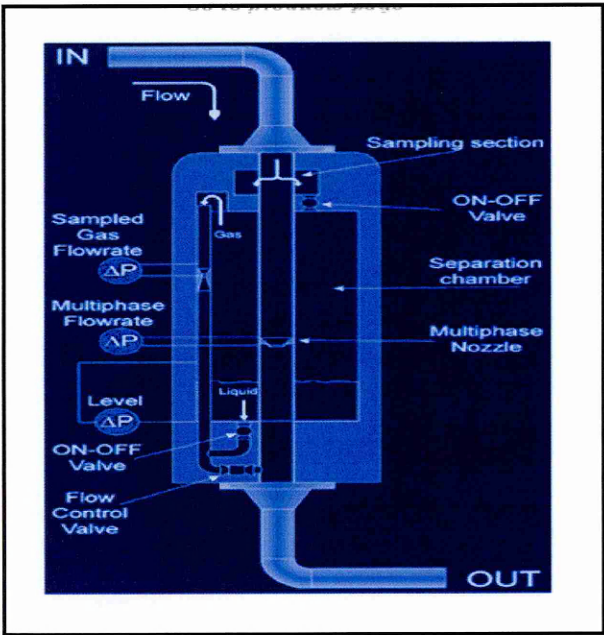
Extended Venturi (OneStep): FMC Energy Systems offer an extended-throat Venturi meter. The differential pressure is measured across the convergent section of the Venturi and also along the length of the extended throat (Figure 2.13). These measurements are combined with a two-phase separated flow model to calculate the liquid and gas flow rates. Initial laboratory tests showed uncertainty of $\pm 4 \%$ for the gas phase and the total mass flow rate and $\pm 5 \%$ for the liquid phase, Fincke et al (1999).

Figure 2.13: Extended Venturi, OneStep taken from Fincke et al (1999).



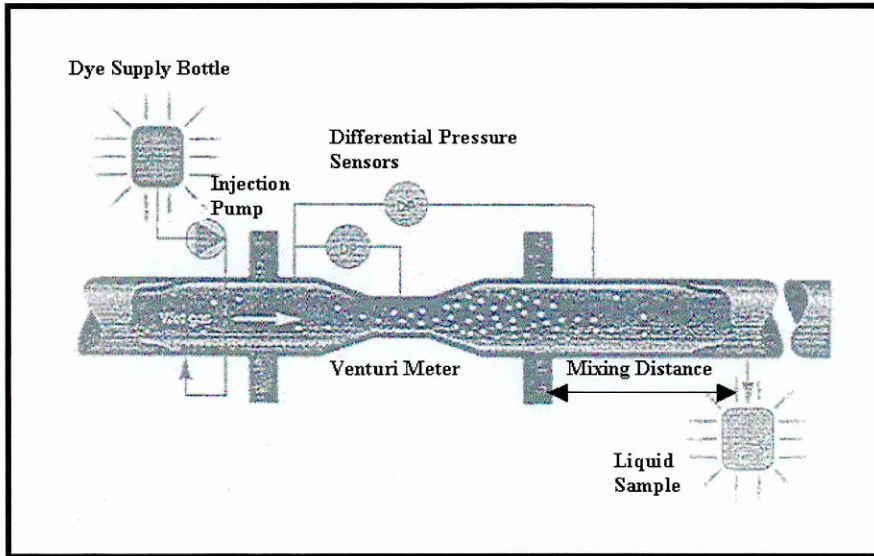
VEGA wet gas Flow meter: Andreussi et al (2000) reported the development of wet gas flow meter known as VEGA by TEA in Italy. The meter working principle is the isokinetic sampling of the gas-liquid mixture, followed by separation and individual metering of the gas and the liquid phase. The liquid flow rate is derived from the value of the sampled liquid flow rate. The gas flow rate is measured with a nozzle. Preliminary experimental tests have shown that both the gas and liquid flow rates can be measured with an error less than 5 %. TEA in Italy manufactures and markets this meter. There are currently no third party performance evaluation reports on this meter. Figure 2.14 is a schematic representation of VEGA.

Figure 2.14: VEGA Wet Gas Flow Meter, taken from Andreussi et al (2000)



SmartVent: This meter (see Figure 2.15) is used in combination with de Leeuw’s wet gas Venturi correlation to correct the over-reading caused by the liquid presence. The liquid flow rate is provided by the tracer dilution technique or by off-site flash calculations. According to de Leeuw et al (2002) there are more than 140 of the Petrotech wet gas meters purchased by various operators worldwide. One major drawback of the tracer technique is that it does not provide online liquid flow rate measurements and requires repeat tests whenever a change in the liquid rate is perceived, which adds to the capital and operations costs of the meter.

Figure 2.15: SmartVent Flow Meter, taken from de Leeuw et al (2002)



Roxar WGM: This metering technology is developed and marketed by Roxar, Norway. It provides three-phase (oil, water and gas) flow rates. It detects the water content based on microwave sensors and flow rates using a Venturi or V-Cone differential pressure meters while using PVT flash calculations for gas and oil fraction derivations. Two solutions are currently available, a V-Cone and a Venturi based version. The V-Cone version is the most compact solution that is integrated in most Subsea modules. The Venturi has the advantage that the geometry is less intrusive and that the need for flow meter calibration is minimised, Lund BØ et al (2002). The meter is planned to be field tested by two oilfield operators, Statoil and TotalFinaElf. The meter has measurement accuracy for the hydrocarbon flow rates of $\pm 3-5\%$. At GVF of 0.91-0.985, water detection accuracy is $\pm 0.2\%$ in cases with WLR $<50\%$, while the water is systematically overestimated and finally fails in the case of water-continuous liquid (WLR $>50\%$).

2.3.2.2 Multiphase Flow Meters (MPFMs)

The difference between multiphase flow and wet gas flow metering is that, in multiphase flow measurement, the flow stream is broken down into three separate phases-oil, water and gas. In wet gas flow measurement, however, the flow stream is broken down into two phases-gas and liquid. The reason for this distinction may be primarily revenue driven, Falcone et al (2001), Agar (2002) and Mehdizadeh (2003). For example, if there is an economical value in the recovery of the liquid phase, which may be the case in gas lift fields, where the operator would want to know the amount of liquid produced as well as the watercut of the liquid produced, then this may be defined as multiphase flow and would require a multiphase flow meter. Gas field or gas condensate operators want accurate measurement of gas produced while the gross liquid measurement is only necessary to make a correction for improved gas measurements, but is not usually concerned about the watercut measurement accuracies of the liquid phase, and hence this would be classified as a wet gas flow measurement problem.

Today several commercially available multiphase flow meters exist which have reached an advanced technical level. Many review publications were encountered in the literature on measurement techniques related to multiphase systems, including those of McNulty and Beg (1997), Yeung et al (1998), Caetano et al (1999) and Lex Scheers (1999), Thorn et al (1999), Falcone et al (2001), Mehdizadeh (2003) and Stobie (2003).

Most multiphase flow meters are limited in their use to between 80-95% GVF, and indeed many manufactures will not quote an expected accuracy beyond 90 % GVF, Andreussi et al (2000), Ting (2001) and Stewart et al (2002). The approach of MPFMs to the problem of multiphase flow measurement may be classified in the following two main categories:

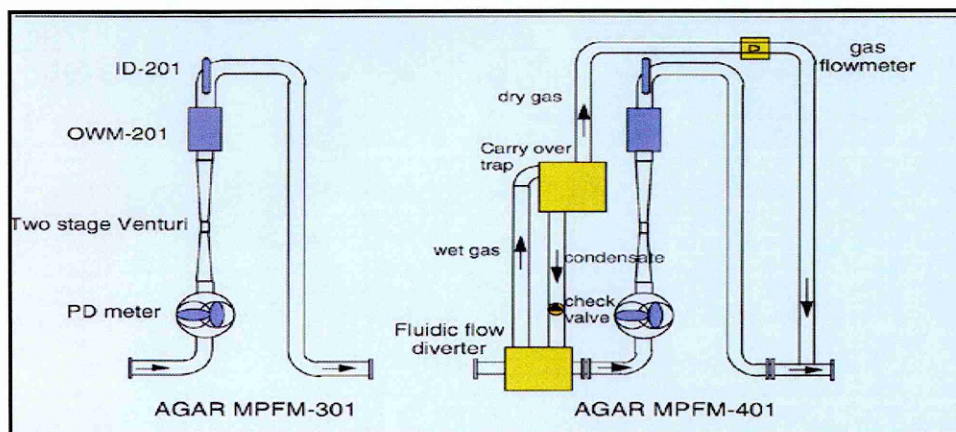
- Phase Separation
- In-line multiphase flow meters

Phase Separation

A methodology to measure high gas volume fraction, multiphase streams has been to utilise existing operational technology for part of the stream, which can handle low GLR and divert the remainder of the gas through a gas measurement leg of the system. Existing MPFMs that use this approach include those of AGAR, WellComp, Accuflow, Kvaerner-CCM, Megra, Haimo and Jiskoot-Starcut.

Tests in recent years at the National Engineering Laboratory (NEL), Glasgow, UK and in the field have shown that separation based systems are less affected by GVF than MPFM, which use other measurement methodologies. The main disadvantages of separation based MPFMs are size, weight and in some cases reliance of fast acting valves for level control in the separator. Hence they are not usually seen as beneficial as inline multiphase flow meters. The Agar MPFM is frequently reported to perform well across the operating envelope of wet gas flow. The AGAR MPFM is a three phase metering system including a Fluidic Flow Diverter (FFD) and a separate leg with liquid knockout and a 2-phase meter (Figure 2.16). The predominantly gas phase is measured in the gas loop, which is sized to handle all the gas. Part of the gas and all the liquids are measured in the part consisting of a Positive Displacement (PD) meter, a Venturi and oil in water monitor (microwave sensor). The total volume is measured by the PD meter, the total mass by the Venturi and the water cut by the oil/water monitor.

Figure 2.16: AGAR MPFM, taken from Al-Taweel and Barlow (1999)



The gas is diverted by the FFD and piped through a cyclonic separator that extracts virtually all the liquids out of the gas loop stream. The liquids are then piped back to the liquid leg of the metering system, where the volumes are measured and included in the total metered volumes. The gas metered through the liquid leg is added to the gas bypass loop for total reported gas.

The Agar multiphase flow meter is said to have performed to its specifications ($\pm 10\%$ of the reading for Gas, Oil and Water) in numerous fields worldwide, up to 99.99 % GVF, McNulty and Beg (1997), Agar (2001). Conoco (USA) have tested the Agar MPFM for high GVF under controlled field conditions on its Lafayette (Louisiana, USA) test loop and found it to be accurate to $\pm 12\%$ compared with reference single-phase measurements, McNulty and Beg (1997). Saudi Aramco have reported trial testing the Agar MPFM at a gas oil separation plant (GOSP), Al-Taweel and Barlow (1999). Here, the plant's separator was used as a reference measurement to evaluate meter accuracy. Approximately 30 comparison tests were made over a wide range of watercuts and GVFs (though the range of GVF was not mentioned). They mentioned that the meter compared well with the test separator and that no significant problems or operational failures occurred. However, the meter tested was said have been undersized for a large portion of the company wells.

In-Line multiphase Flow meters

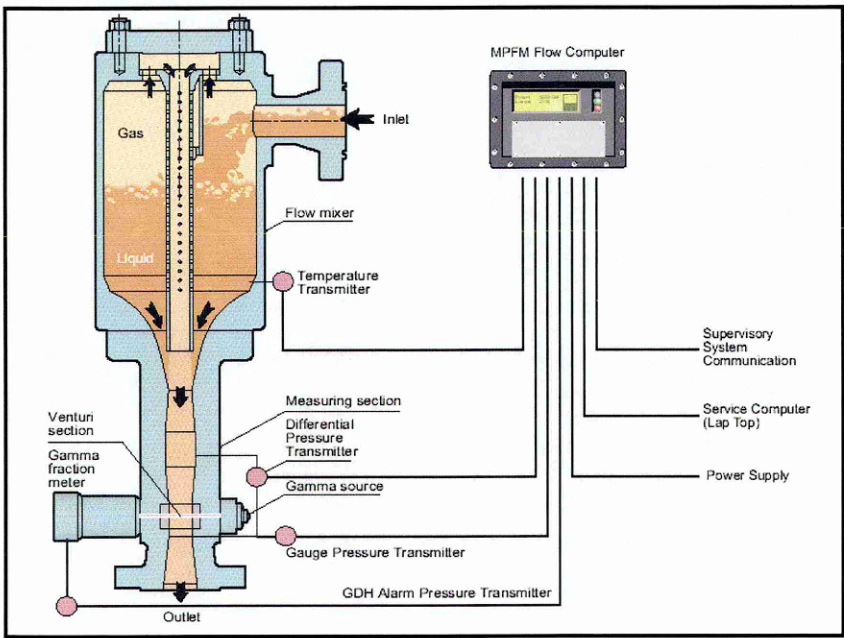
Given below is a brief discussion on in-line multiphase flow meters. These are further subdivided into two categories: those that utilise static mixers and those that do not have static mixers in their set up.

MPFMs with Static Mixers

The principal supplier of operational multiphase meters, utilising this technology include those of Jiskoot-Mixmeter, Schlumberger-Framo, TEA-Lyra and ISA-Multistream, Falcone et al (2001).

With this approach, prior to any measurement, the liquids and gas are homogeneously mixed and forced through the measurement section in a single (no slip) velocity, hence a single, mixture flow rate measurement is all that is required. In order to determine the relative proportion of liquids and gases, gamma ray sources of two different energy levels are utilised: one for determining the watercut and the other for determining the GVF. With known approximation of densities of the produced water, condensate and natural gas, the relative fraction of each phase can be determined and the flow rate of each solved. Amongst the flow meters that require flow pre-conditioning and mixing, the Framo-Schlumberger MPFM has been field tested and used for high GVF (up to 98%). As shown in Figure 2.17 this meter consists of three primary components: a static flow mixer to homogenise the flow and eliminate any flow regime effect, a Venturi section to measure the bulk of flow through the meter and a Gamma ray absorption meter, imbedded in the throat of the Venturi to provide the volume fractions of oil, water and gas in the flow

Figure 2.17: Framo-Schlumberger MPFM, taken from McNulty and Beg (1997)



The Framo-Schlumberger MPFM was tested in many different sites around the world, including both engineering laboratories and field trials, Letton et al (1997) and Stobie

(2003). This meter was installed and applied on three wellhead platforms of the BHP Liverpool Bay in the North Sea, which particularly had a high GOR, and the actual GVF was in the range of 0.85-0.98. East Spar Alliance in Australia have also deployed a number of these MPFMs with operating GVF of up to 0.95 in their offshore fields. The actual measurement accuracies obtained were not reported, but the meters were said to be operating to the operator's satisfaction with no major technical or operational problems reported, Letton et al (1997).

The TEA MPFMs cannot be satisfactorily used for wet gas metering, mainly because the errors affecting the measurement of the total liquid flow rate and the watercut goes well over 10% when the GVF is above 90%, Andreussi (2000).

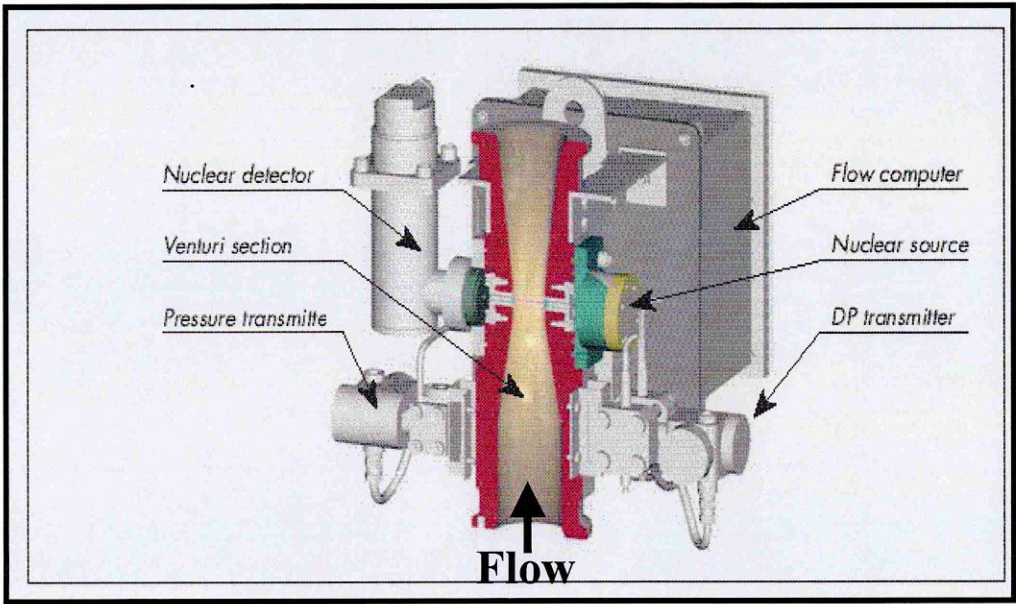
MPFMs without Static Mixers

The commercially available MPFMs that do not require flow conditioning (i.e. neither inline mixer nor separation) prior to metering include Schlumberger-VX, Roxar-Fluenta, Roxar-MFI, Kvaerner-DUET, FlowSys and ESMER

The above MPFMs (except ESMER, which is discussed later under section 2.4.5) rely on a number of fluid property measurements combined to give the individual, gas, and oil and water flow rates. It is worth mentioning that many of the MPFMs mentioned under this category require an upward vertical flow installation, preceded by a blind-tee, the function of which is to condition the phase distribution of the flow (i.e. mix) so that a single, homogeneous, bulk flow rate, can be determined based on either Venturi meter or cross-correlation techniques. The phase fractions are usually determined from measurements of physical properties of the three-phase mixture from which the relative quantities of each individual phase can be determined. The methods used for phase fractions include Gamma densitometry, capacitance/conductance sensors and microwave techniques. The velocity/flow rate measurements are most commonly achieved using differential pressure devices (Venturi, orifice) or cross-correlating the signals of two sensors.

The Schlumberger-VX MPFM (two versions are available, one for periodic well testing and for permanent monitoring) consists of a classical Venturi meter for measuring the bulk (mean) fluid flow in an upward vertical flow section and a dual energy gamma-ray compositional meter at the throat of the Venturi meter for measuring oil, water and gas fractions (Figure 2.18).

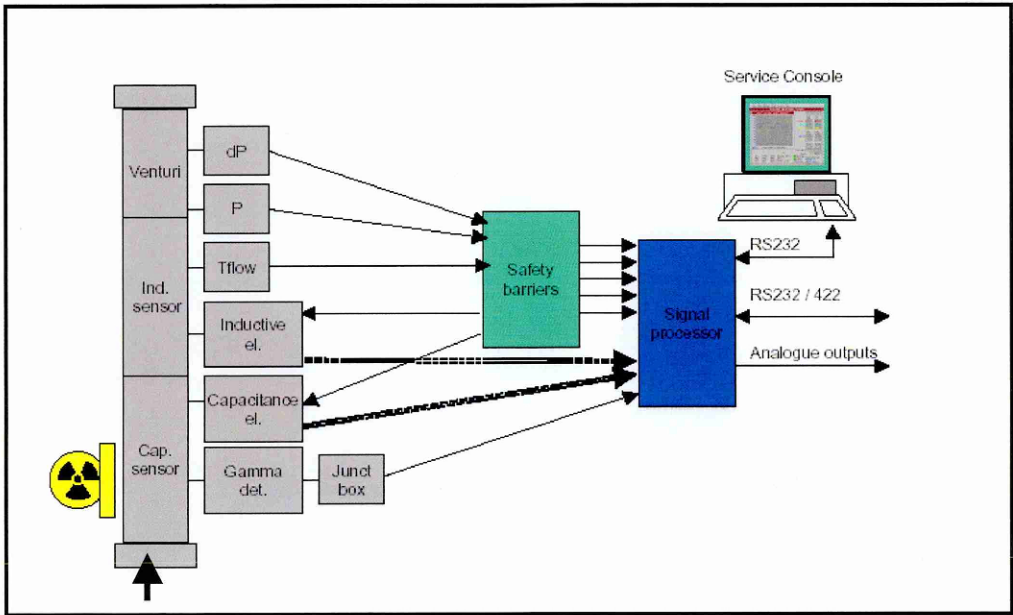
Figure 2.18: Schlumberger-VX MPFM, taken from Theuvent et al (2001)



According to Theuvent et al (2001) 415 well tests were performed using this meter in 12 different countries. The GVF ranged from almost 0 to almost 100% with over half of the wells tested over 85 % GVF. It was mentioned that for the dry natural gas wells, the meter could not provide reliable results for the liquid phase measurements, as levels of liquid as low as a few BBL/MMSCF were detected, which was said to be outside the operating range of the meter. The operating range of this meter is quoted to be limited to 98% GVF, this to maintain a relative accuracy of the liquid flow rate of $\pm 3 \%$; above this limit, the meter would of course still continue to provide liquid information, but its accuracy is said to suffer a gradual deterioration. Above the operating range of the meter, it was possible to utilise the meter as a trending/qualitative instrument to monitor the general trend of the flow.

The Roxar-Fluenta 1900 VI MPFM has been field tested at high GVF. As shown in Figure 2.19, this meter consists of capacitance and conductivity sensors, which are used for phase fraction measurements, in conditions of oil and water continuous mixtures respectively. A cross-correlation of the capacitance sensors is used for flow rate measurement with the mean density of the mixture measured by the gamma densitometer. A Venturi meter is also included in the meter set-up to measure mass flow rates and extend the operating range of the MPFM into single-phase flow, where cross-correlation techniques fail to operate. The installation is usually in vertically upward flow.

Figure 2. 19: The Roxar-Fluenta MPFM 1900VI, taken from Dykesteen (1999)



Legget et al (1996) reported that this meter was field-tested by Gulf of Suez Petroleum Company (GUPCO) in the Gulf of Suez, Egypt. The flow regimes observed during the field test of this meter ranged from severe slugging to annular flow due to the dynamics of gas-lift gas in the production stream. Average gas volume fraction ranged from 93-98 % during tests conducted on seven wells. The meter was placed in series with a test separator located on a nearby production platform. It was reported that the MPFM measured gas and liquid flow rates to within ± 10 % of the test separator and accomplished this at GVF from 93-96 %. In some of the wells, the liquid rate was found to be significantly outside the ± 10 % error band, because of an annular flow regime and

a very high GVF average of 97-98 %. Although, the MPFM's measurement accuracy was significantly reduced in these conditions, nevertheless it provided consistent and repeatable results, which could be used for flow condition and trend monitoring.

Al-Taweel et al (1999) reported that Saudi Aramco has field-tested the Roxar-Fluenta 1900 VI MPFM. The MPFM was trial tested at two different onshore gas and oil separation plants (GOSP). The meter was tested over a range of flow conditions, liquid rates of 1 to 15 MB/D, watercuts of 0 to 80 % and GVF of 50 to 90+%. For wells with below 90 % GVF, the meter performance was considered acceptable (within ± 10 % for liquid rate, ± 15 % for watercut and ± 15 % for gas rate), however the meter's performance over 90 % GVF was said to be poor.

2.3.2.3 Factors Affecting MPFMs Performance in Wet Gas Flow

It can be deduced from the foregoing test and performance results of MPFMs that accurate measurement of high GVF multiphase flow is a clear challenge for commercially available MPFMs. The measurement accuracy particularly worsens for the liquid phase as GVF increases beyond 98 %, to the extent that the meter's accuracy cannot be relied on, and the MPFM has to abandon its primary purpose of flow measurement and may be used as a general flow and trend-monitoring device, Legget et al (1996) and Theuvent et al (2001).

The difficulty in multiphase flow measurement at high GVF is primarily caused by the nature of the flow. For a typical multiphase flow at high GVF (>90 %), the multiphase transport may be dominated by an annular flow regime, which is complicated and causes measurement problems. Such flows are characterised by a liquid film flowing along the pipe wall and a gas core containing entrained liquid droplets. In horizontal flow, the film thickness will be maximum at the bottom of the pipe because of gravity effects and the force exerted on the droplets by the gas core is larger than or equal to the gravitational

force, otherwise the liquid droplets would join the liquid film and form a different regime, such as slug or wavy flow.

In vertical upward flow, which is the typical arrangement in most of the in-line MPFMs, the film thickness will be radial symmetric. The liquid droplets from the gas core are continuously deposited on the liquid film, and droplets are torn off from the film and mixed with the gas, Lopes et al (1986). In some instances, the liquid film momentum would be too low and the liquid gas may travel at opposite directions in an annular bi-directional flow, Fairclough (2000).

In-line MPFMs use one of two techniques for the determination of the total fluid flow rate: cross-correlation or Venturi meters, and use mainly gamma densitometers for phase fraction measurements. The major underlying assumption in flow rate measurement techniques is that all phases are moving at the same velocity by attempting to homogenise the flow by either static mixers or blind-tees, hence a single velocity/flow rate measurement is all that is required. However, while homogenisation may be effective at liquid continuous conditions with low GVF, it becomes practically difficult to create or sustain at high GVF, typically above 90 %, Claudio et al (2000), Falcone et al (2001, 2003).

The cross-correlation technique is used to determine the velocity of disturbance (for example liquid droplet in the gas) and correlate the variation in some property of the fluid between two identical sensors of any technology (e.g. capacitance, conductance, ultrasonic, pressure, microwave, etc) separated by a pre-defined distance on a straight pipe section (in the direction of the flow). The statistical comparison of the measurements on the first and second sensors enables the determination of the transit time, which the mixture spends to move between the two sensors. As the distance between the sensors is known, the mixture velocity in the meter can be measured. This technique was originally designed and successfully applied to single-phase liquids, and was later applied to multiphase flow mainly in the liquid continuous systems.

In the case of wet gas flow, however this technique has some severe technical problems. In the Annular flow regime the eddies or disturbances may be represented by the liquid droplets/entrainments in the gas core, which may be roughly approximated to have similar velocity as the gas core, but by no means have the same velocity as the majority of the liquid represented by the liquid film.

Other in-line MPFMs use Venturi meter to estimate the total fluid flow rate and gamma densitometer to calculate the phase fractions. In doing so they also assume that the multiphase flow mixture (oil, water and gas) travels with the same velocity (in a homogeneous mixture), and hence apply standard Venturi relationship with a multiphase mixture density to calculate the mixture flow rate. However as mentioned earlier there are currently no flow conditioners that can achieve perfect homogeneous flow mixture in the annular/mist flow regime. Furthermore the use of a gamma densitometer to deduce the phase fractions in high GVF multiphase flow has some technical limitations. Gamma densitometers are known to function satisfactorily in liquid continuous flows, where they can distinguish between the respective liquid phases (e.g. oil and water), whose absorption coefficient for the gamma rays differ by a relatively small amount. However if the gamma densitometer is calibrated in dry gas and then exposed to annular mist flow, it suffers an accuracy problem as the energies/intensities of the gamma rays in dry gas and wet gas at GVF above 98 % are almost the same, and the small amount of liquid does not attenuate the nuclear counts sufficiently to provide a good contrast and secondly the generation of gamma rays has a significant randomness resulting in large errors at high GVF, Wood (2002). The flow sensors (pressure, capacitance, conductance, etc) that are designed initially to function in liquid continuous multiphase flow may also be operating on the edge of their operating envelope, when it comes to annular mist flow and hence may be exacerbating the measurement uncertainties of multiphase flow meters in this region.

In addition to their low accuracy in wet gas flow, multiphase flow meters are relatively costly. The capital expenditure of current multiphase flow meters is approximately \$100,000-300,000 plus, Scheers et al (2002). This is still an order of magnitude cheaper

than a test separator, however for the development of marginal fields with approximately 5-10 wells or more, MPFM installations per well are difficult to justify. Hence there is an urgent need in the oil and gas industry to find more accurate and cost effective techniques, dedicated to wet gas flow measurement.

The forgoing sections and discussions of this chapter have provided a state-of-the art review of the current technologies available for wet gas flow measurement, together with the technical challenges still remaining to be tackled in this difficult subset of multiphase flow. The available literature highlighted that multiphase flow does not fully lend itself to conventional fluid modelling techniques. The responses from instruments do however inherently contain all the information they have gathered about the process. By capturing the information emerging from the sensors and with the use of advanced techniques of signal processing and pattern recognition, it may well be possible to infer the individual phasic flow rates and provide online/real time flow condition monitoring.

The remaining sections of this chapter will review the technologies of signal processing and pattern recognition as relevant to the current research work and scope of work

2.4 The Pattern Recognition Approach

The following sections of this chapter are intended to serve as an introduction to various signal processing and pattern recognition techniques as relevant to the current research work and related previous studies.

Humans are very good at recognising and classifying information and thereby extracting knowledge from their surrounding environment. In doing so, we do not usually analyse the different situations of the real world as isolated facts, but we try and describe them in terms of *patterns* of related facts. Some times these relations are implicit because they all refer to the same object. Some other times, however, it is necessary to explicitly connect these characteristics in order to find a relation. Part of the motivation for the study of pattern recognition, therefore, stems from the desire to understand the human pattern recognition and reasoning capabilities.

Fluid flow measurement accuracy is often limited by our understanding of the fundamental laws governing flow processes and is further exacerbated by the complex nature of multiphase flow, which does not fully lend itself to conventional fluid modelling techniques. The responses from instruments do however inherently contain all the information they have gathered about the process.

Pattern recognition aims to classify data (patterns) based on either a prior knowledge or on statistical information extracted from the patterns. The patterns to be classified are usually groups of measurements or observations, defining points in an appropriate multidimensional space. A complete pattern recognition system consists of three major steps; i) a sensor that gathers the observations to be classified or described; ii) a feature extraction mechanism that computes numeric or symbolic information from the observations, and iii) a classification or description scheme that does the actual job of classifying or describing observations relying on the extracted features.

2.4.1 Signal Processing

Signal Processing is concerned with the design, analysis, and implementation of systems that extract information of interest from available data. The theory of signal processing draws upon ideas from probability and statistics, information theory, digital filtering, spectral representation and analysis. Recent rapid advances in digital signal processors, computer systems, and integrated circuit technology have all facilitated the development of sophisticated signal processing techniques and advances in many fields such as seismic, medical, sonar, radar and speech recognition.

Signal processing commences with data collection by a sensor, which usually outputs a continuously varying voltage waveform (analogue). The analogue waveform is then converted to digital format by sampling it at an appropriate sampling interval in order to implement mathematical signal processing techniques on computers.

A fundamental theorem of signal processing states that a signal can only be constructed accurately from a sampled version if it does not contain components, whose frequency is greater than half the frequency at which the sampling takes place, Oppenheim, et al (1997).

The sampling frequency f_s can be defined as follows: -

$$f_s = 2f_N \quad (2.19)$$

Where f_N is the Nyquist frequency, which is the highest frequency below which meaningful information from a set of data can be obtained. If a waveform is sampled at less than twice its sampling frequency the reconstructed waveform will effectively contribute only noise. This phenomenon is called "aliasing" (the high frequencies are "under an alias").

A classical example of aliasing can be seen when filming rotating objects, like wheels and aeroplane propellers. The film ‘samples’ is at a fixed rate, while a wheel can rotate at different speeds. As the wheel exceeds the Nyquist frequency it appears to rotate backwards.

2.4.2 Feature Extraction

Given a digital representation of the signal, various parametric representations can then be derived. In order to utilize all information from time-developing signals in multiphase flow, it is possible either to use all the data points in the analysis, or to find some features (typically much fewer than the number of data points) that makes it possible to represent all the information in the measurement. For many PR applications, the discovery and selection of an effective feature set is the most important and difficult part of the problem. The difficulties in selecting effective features are due to several facts. First, it is necessary to select a feature combination that separates the class volumes so that the classes can be distinguished, but this property of a feature set is not generally obvious without carrying out a PR or data visualization analysis of the training set using the selected features. Second, there are often many features, and combinatorially large numbers of feature combinations, to select from. If too many features are used for the classification, there is a risk that the pattern recognition model gets too complex, and the generalisation capability of the model (i.e. the ability to correctly classify new data) can then be poor. It is therefore useful to reduce the number of original data points to a few sets of features that can represent the system.

These features can be from a number of information domains, mostly from time domain or frequency domain. In the following sections, a brief description of some the features that can be extracted from the raw signals emerging from multiphase flow conditions will be given.

The most common difficulty in pattern recognition is usually the vast amount of information, which has to be dealt with. It is evidently advantageous if one can reduce this massive information into manageable proportions by isolating and extracting just that part of the information, which is relevant for the recognition process, from the mass of irrelevant information, which often accompanies it. The definition, extraction and selection of this useful information are the main concern of the following sections.

2.4.2.1 Moments of the Amplitude Distributions

The Probability Density Function defines the probability that a sampled signal will assume a particular value within some range at any instant time. The probability density function, $P(x)$ can be defined as follows: -

$$\begin{aligned}
 P(x) &= \lim_{\Delta x \rightarrow 0} \frac{\text{Prob}(x < x(t) < x + \Delta x)}{\Delta x} \\
 &= \lim_{\Delta x \rightarrow 0} \frac{1}{\Delta x} \left(\lim_{T \rightarrow \infty} \frac{T_x}{T} \right)
 \end{aligned}
 \tag{2.20}$$

Where $P(x)$ is the probability density function of a sample time history record $x(t)$, T_x is the total time during, which the signal assumes a value between x and Δx .

The probability density function is mainly used to describe the probabilistic distribution of instantaneous values of continuous random data. However, the distribution of a signal is not a unique property and no information about signal structure is given. Instead, sets of properties known as moments of distribution function are obtained from the amplitude variation to describe the signal.

One of the most important and most fundamental concepts associated with statistical methods is that of finding moments of random variables. These are the mean, standard deviation, the coefficient of skewness, coefficient of kurtosis and coefficient of variation, Johnson (1994).

The mean ($\bar{x}$), is the arithmetic average value of the data points, and it estimates the value around which a central clustering occurs.

$$\bar{x} = \frac{\sum_{i=1}^N x_i}{N} \quad (2.21)$$

Where x is the amplitude value of the i^{th} point and N is the number of points in the sampled record.

The standard deviation is the root mean square of the amplitude deviations from the arithmetic mean and is a measure of the dispersion of the data. The standard deviation, SD is defined as:

$$SD = \sqrt{\frac{\sum_{i=1}^N (x_i - \bar{x})^2}{N-1}} \quad (2.22)$$

The coefficient of skewness characterizes the degree of asymmetry of the distribution around its mean. A positive (negative) value of the skewness implies a distribution with a higher number of large (small) values of the parameter than would be expected for a Gaussian distribution. The coefficient of skewness, CS, is defined as: -

$$CS = \frac{\sum_{i=1}^N (x_i - \bar{x})^3}{(N-1)SD^3} \quad (2.23)$$

The kurtosis measures the relative peakness or flatness of a distribution compared to a normal distribution, with the same mean and standard deviation; the larger the kurtosis, the more peaked the distribution. The coefficient of kurtosis is defined as: -

$$CK = \left(\frac{\sum_{i=1}^N (x_i - \bar{x})^4}{(N-1)SD^4} \right) - 3 \quad (2.24)$$

The skewness and kurtosis are non-dimensional moments, contrary to the mean and standard deviation, which have the same dimension as the measured quantities. For a Guassian distribution, the skewness and kurtosis are zero.

Another non-dimensional quantity is the coefficient of variation. It measures the scatter in the data distribution in relative terms by dividing the standard deviation by the mean of the data. The coefficient of variation, CV is defined as: -

$$CV = \frac{SD}{\bar{x}} \quad (2.25)$$

Another useful feature that is not related to the probability density function, but can be extracted from the time series of the signal is the signals total energy. In many applications the signals we consider are directly related to physical quantities capturing energy in a physical system (e.g. signals generated from multiphase flow). The total energy in a discrete-time signal $x(n)$ over the time interval $n_1 \leq n \leq N$ is given below.

$$E_T = \frac{\sum_{n=n_1}^N (x_n)^2}{N} \quad (2.26)$$

2.4.2.2 Linear Prediction (LP) Coefficients

Linear prediction coding is one of the common speech coding techniques, which exploits the redundancies of a speech signal by modelling the speech signal as a linear filter, excited by a signal called the excitation signal. The excitation signal is also called the residual signal. Speech coders process particular group of samples, called a frame or a waveform. The speech encoders find the filter coefficients and the excitation signal for each frame. The filter coefficients are derived in such a way that the energy at the output of the filter for that frame/waveform is minimised. In physical terms LP coefficients contain unique information on the spectral content of the waveform, which is generated by a physical process (speeches, multiphase flow, etc) and capture the variations in energy and spectral characteristics in short time interval. Since LP coefficients provide a simple and effective method of representing different signals in terms of small number of parameters, they can be used not only as a way of data compression but also as a supply for different statistical features for different signal conditions, Makhoul (1975).

Linear prediction can be modelled in the time-domain by minimizing the sum of the squared differences (over a finite time interval) between the actual signal samples and the linearly predicted ones resulting in a residual error. In doing so, a set of unique predictor coefficients, which are the weighting coefficients used in the linear combinations are determined.

The present signal sample $x(n)$ is modelled as a linear combination of the past outputs and the present and past inputs, Makhoul (1975). This relationship can be expressed in the following difference equation:

$$x(n) = \sum_{k=1}^p a_k x(n-k) + G \sum_{l=0}^q b_l u(n-l), \quad b_0 = 1, \quad (2.27)$$

Where G is a gain factor and a_k and b_l are the filter coefficients of some unknown input u_n . The number p implies that the past p output samples are being considered, which is also the order of the linear prediction. The transfer function $H(z)$ of the system is obtained by applying a z -transform on equation (2.27).

$$H(z) = \frac{X(z)}{U(z)} = G \frac{1 + \sum_{l=1}^q b_l z^{-l}}{1 - \sum_{k=1}^p a_k z^{-k}} \quad (2.28)$$

Where $X(z)$ is the z -transform of $x(n)$, $U(z)$ is the z -transform of $u(n)$, and $H(z)$ is the transfer function of the system, which is the general pole-zero model. There are two special cases of this model, which are: 1) when $a_k = 0$, for $1 \leq l \leq p$, $H(z)$ reduces to an all-pole model, which is also known as an *autoregressive* model; 2) when $a_k = 0$, for $1 \leq k \leq p$, $H(z)$ becomes an all-zero or *moving average* model. The all-pole or autoregressive model is widely used for its simplicity and computational efficiency. To solve the pole-zero model, it is necessary to solve a set of non-linear equations, but in the case of an all-pole model, only a set of linear equations need to be solved. A by-product of the linear prediction technique is the generation of the residual error, $e(n)$ which is the difference between the input signal and the estimated signal. Thus the following relationship holds.

$$e(n) = x(n) - \sum_{k=1}^p a_k x(n-k) \quad (2.29)$$

A simple test to obtain the optimal linear predictor order p is to check the variation of the residual error with the predictor order, which will almost be flat for $p > p_o$, where p_o is the optimal linear predictor order.

There are two widely used methods for estimating the LP coefficients, which are the autocorrelation and the covariance method, Golub et al (1989). Both methods choose the short-term filter coefficients in such a way that the residual error is minimised using the

least square technique. When the autocorrelation method is used a Toeplitz matrix, where all elements along a given diagonal are equal is generated which unlike the covariance method guarantees the stability of the synthesis filter. This allows the linear equations that arise from the least-squares formulation to be solved by the Levinson-Durbin recursion algorithm, presented by Golub et al (1989).

The relationship between two random variables called correlation, gives a measure of the average dependency of the two signals. The correlation between pairs of signal sample is known as an autocorrelation (AC). The autocorrelation function of a signal is an average measure of its time domain properties given by:

$$r_{xx}(\tau) = \lim_{T \rightarrow \infty} \frac{1}{T} \int_{-T/2}^{T/2} x(t)x(t+\tau)dt \quad (2.30)$$

Where r_{xx} is autocorrelation function, τ is time shift known as lag. When the autocorrelation technique is used to compute the LP coefficients as described above, the sample correlation function can be calculated first. There are no requirements to do extra calculations to obtain the autocorrelation coefficients, AC.

2.4.2.3 Other Representations of LP Parameters

Linear prediction coefficients (LP coefficients) have other representations: line spectral frequencies (LSF), reflection coefficients (RC), log area ratio (LAR), arcsine of reflection coefficients (ASRC), impulse response of LP synthesis filter (IR), etc. They effectively have a one-to-one relationship with the LP coefficients, and they preserve all the information from the LP coefficients. Among them, the LSF have been shown to be most computationally efficient and has better quantisation and interpolation properties, which leads to a better system approximation (e.g. improved speech quality), Deller et al (1994).

Line spectral frequencies were found to encode speech spectral information more efficiently than other transmission parameters. This is attributed to the intimate

relationship between the LSFs and the formant frequencies. In addition, LSFs lend themselves to frame-to-frame interpolation with smooth spectral changes because of their frequency domain interpolation, Kabal et al (1986).

The prediction error filter or the LP analysis filter $A(z)$ could be expressed in terms of the LP coefficients (direct form predictor coefficients) a_k in the following form:

$$A(z) = 1 - \sum_{k=1}^p a_k z^{-k} \quad (2.31)$$

Where p is the order $A(z)$. The $(1+p)th$ order symmetric and anti-symmetric polynomial $P(z)$ and $Q(z)$ can be obtained from $A(z)$:

$$P(z) = A(z) + z^{-(p+1)} A(z^{-1}), \quad (2.32)$$

$$Q(z) = A(z) - z^{-(p+1)} A(z^{-1}), \quad (2.33)$$

The roots of the two polynomials lie on the unit circle and they form the line spectral frequencies (LSFs). Kabal et al (1986) presented an algorithm, which computes the LSFs directly from the LP coefficients using the Chebyshev polynomial root finding method. The signal processing toolbox of MATLAB includes a routine, which finds the roots of the above polynomials using the Chebyshev polynomial root finding method described by Kabal et al (1986).

Line spectral frequencies (LSFs) are commonly used to estimate features for speech recognition algorithms. LSFs can also be implemented in the field of multiphase flow since they can be used to decompose the original signal into small number of parameters. LSFs will for the first time be evaluated in the current research for their effectiveness to discriminate different flow conditions in multiphase and wet gas flow conditions.

2.4.2.4 Pre-Processing and Dimensionality Reduction

There are number of feature pre-processing techniques available in the literature. One method is to normalise the input features to the pattern classifier so that they fall in the range of $[-1, 1]$. Another normalisation technique is to equalise the magnitude and dynamic range of each feature by applying zero mean and unit-variance normalisation to the feature vectors. Here the data values are centered (i.e. subtract the mean values from the data values in order to obtain centered anomalies) and then divided by their standard deviations to obtain a normalised data having zero mean and unit variance.

In certain situations, further feature pruning may be necessary, where the extracted and normalised features require dimensionality reduction. The process of selecting and extracting features from high dimensional data that can be used to discriminate the underlying classes, or identify the target from non-targets is referred to as dimensionality reduction. The motivation behind performing a dimensionality reduction is usually to remove the redundant information present in the data and reduce the computational complexity.

There are many different dimensionality reduction techniques, which may be broadly classified into two categories. In the first case, the relevant features are selected from the raw data in its original domain based on some discriminatory criterion. From a classification perspective, the objective of this criterion is to select those features that have a higher discriminatory capability of the system. The feature contour maps superimposed on two-dimensional system variables used to guide the feature selection process is an example of this category.

In the second case, the features are transformed into a new feature domain, where they can be arranged in the order of their importance, which is application specific. The transformation techniques include linear discriminate analysis (LDA), Webb (1999), discrete wavelet transforms (DWT), Mallat (1989), and principal component analysis (PCA), Jackson (1991). Amongst these, the PCA is commonly used in a wide range of

applications, including document analysis, data mining, content-based image retrieval, face recognition, speech analysis and spectral remote sensing. PCA is used to reduce a high dimensional vector to a low dimensional vector by exploiting the correlation existing in the data. PCA uncorrelates the resulting components, and the lower-order components are discarded.

PCA involves generating a new set of variables, called principal components.

The first step in PCA is to calculate the data covariance matrix Σ :

$$\Sigma = \sum_{p=1}^P (x^p - \mu)(x^p - \mu)^T \quad (2.34)$$

Where P is the number of vectors in the data set and μ is the mean vector for the data set. The eigenvectors and eigenvalues of Σ are then calculated and ordered according to their variance. The eigenvectors corresponding to the largest eigenvalues are retained, and the input feature vectors are subsequently projected onto these eigenvectors to give the components (Principal Components) of the transformed vectors in the m -dimensional space. An orthogonal basis is extracted from the original feature vectors, which comprise the input space; hence all the principal components are orthogonal to each other. By having the vectors with the greatest information content (variability) ranked first, it is possible to decide when there is no benefit in extracting more vectors.

2.4.3 Pattern Recognition (PR) Models

Once a set of features has been selected, the next problem to be solved is to find a mapping from the components selected to the desired targets. The exact form of this mapping is to be determined from a data set of labelled examples. The procedure for constructing such a mapping is facilitated by the use of a particular pattern recognition model, which is the discussion of the next subsections. Many techniques are currently in use for solving pattern recognition problems. The most well known of these are:

- Artificial Neural Networks (ANN)
- Statistical Models
- Fuzzy Logic
- Expert Systems

There is considerable overlap between the different pattern recognition approaches. For example artificial neural networks can be viewed as an extension of conventional techniques in statistical pattern recognition, Tarassenko (1998), Bishop (1995a). The ability of neural networks to create non-linear decision boundaries as a result of relatively simple training procedures has made it possible to solve hard pattern recognition or signal processing problems, which traditional statistical pattern recognition techniques were not suited to solve adequately. Fuzzy logic techniques have also similar types of logical rules as that used in Expert systems and there is a considerable interest in the combination of fuzzy logic and neural technologies.

2.4.4 Artificial Neural Networks

Artificial neural networks (these are commonly referred to as neural networks or pattern recognition models, and we will be using these three terms interchangeably throughout this thesis) with their ability to derive meaning from complicated or imprecise data can be used to extract patterns that are too complex to be noticed by conventional computing techniques.

Neural networks take a different approach to problem solving to that of conventional computers. Conventional computers use an algorithmic approach i.e. the computer follows a set of instructions in a fixed sequential order to solve a problem. Unless the specific steps that the computer needs to follow are known, the computer cannot solve the problem. That restricts the problem solving capability of conventional computers to problems that we already understand and know how to solve.

Neural networks process information in a similar way to the human brain. The network is composed of a large number of simple, highly interconnected processing elements (neurons) working in parallel to solve a specific problem. A major advantage of neural networks is that they do not have to be programmed, but instead they can learn to form distributed representations of complex relationships from examples (learning refers to the process of weight adaptation, whereby the mean square errors at the output of the network is minimised). The examples (feature vectors) must be selected carefully otherwise useful time is wasted or even worse the network might be functioning incorrectly.

On the other hand, conventional computers use a cognitive approach to problem solving; the way the problem must be resolved must be known and stated in an unambiguous instructions. These instructions are then converted to a high-level language program and then into machine code that the computer can understand.

Neural networks have been applied to a wide variety of different application areas. Hagan et al (1996) gives a good review of these areas. Artificial neural networks have been described exhaustively in the literature, e.g. Lippmann (1987), Bishop (1995a), Hagan et al (1996), so the reader is referred to these references for the fundamental concepts.

The most developed and widely used neural networks include the following:

- Feedforward Multi layer perceptron (MLP)
- Generalised Regression neural networks (GRNN)
- Radial Basic Function Networks
- Learning Vector Quantisation Functions
- Auto-Associative Networks
- Recurrent Networks
- Kohonen Self Organising Feature Map (KSOFM)

As noted earlier neural networks learn from experience, and learning methods may be broadly grouped as supervised and unsupervised, with a great many paradigms implementing each method. For supervised learning, during training the available data samples are labelled to show the class to which they belong, so when an input is applied that results in an output response, this response is compared with a prior desired output. If the output response is different from the target response, the network generates an error, which is then used to calculate the adjustments that should be made to the networks weights so that the actual output matches the target output. In unsupervised training, the weights are modified in response to network inputs only, such that an attempt is made to discover any underlying structure in the data using clustering analysis, which categorise the input patterns into a finite number of classes.

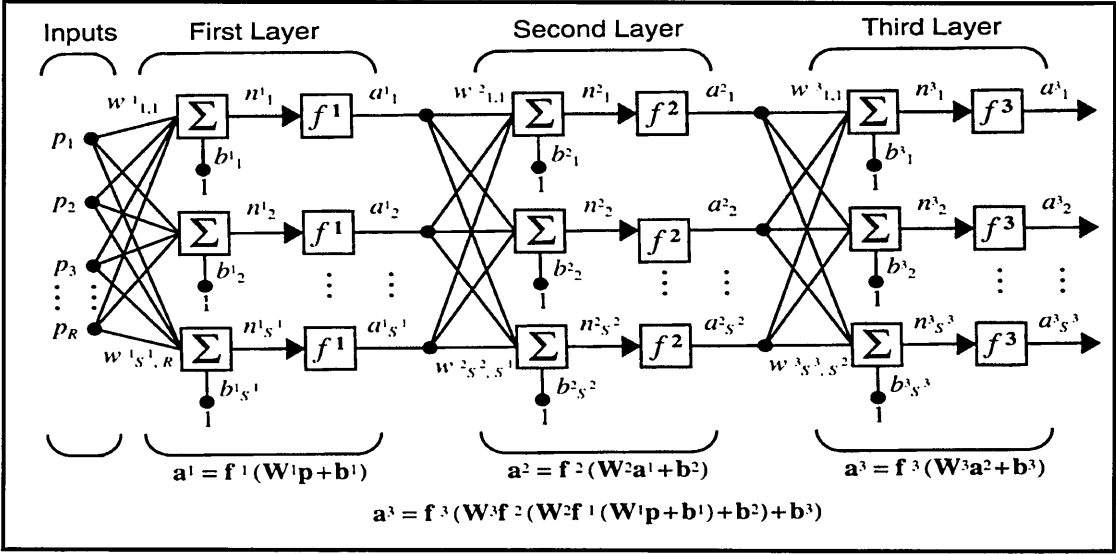
In the current research supervised neural networks have been evaluated, whereby the superficial gas and liquid velocities are used as the target vectors during training. Hence the following discussion will be confined to these techniques.

Learning consists of adjusting the weights so that the neuron performs the classification task correctly (or as close as possible to it). In order to arrive at a weight set which solves the problem, we use error feedback to adjust the weights during training.

2.4.4.1 Multi Layer Perceptrons (MLP)

It was shown in the 1960s that a single layer of perceptron could not learn how to compute the parity of a binary input pattern, Tarassenko (1998). It was then recognised that having several perceptrons operating in parallel could solve the problem. The output of one perceptron would become the input to another perceptron, i.e. by adding a second layer to the network and creating a *multi layer perceptron*.

Figure 2.20: Multi Layer Perceptrons, taken from Neural Network Manual of MATLAB



As shown in Figure 2.20, every input and output variable is represented by an input node, which is connected to all nodes in the hidden layers. Through training, these connections are assigned independent weighting factors. The input to each node is multiplied by its associated weighting factor and then summed with the product of each of the other input nodes and their respective weighting factors. An activation threshold is then subtracted from this sum, and the result is processed by a non-linear transform function within the node.

The neural network learns to infer the relationship between the input and output by iteratively adjusting the weighting factors in a two-stage propagate/adapt cycle. In the first stage of this cycle, the output values are propagated through each layer of the

network until an output is generated. The weighting factors are initially random so that the input values are transformed to the output values, but with no meaningful pattern. These outputs are then compared to the desired output, and an error signal is calculated. This process is known as feed-forward routine. In the second stage, the error signals are fed back through the network and the weighting factors are corrected according to the back-propagation algorithm, and this cycle is iteratively executed until the weighting factors converge on values that minimize the Least Mean Square (MSE) error for all cases within the data set.

$$MSE = E_D = \frac{1}{N} \sum_{i=1}^N (t_i - a_i)^2 \quad (2.35)$$

Where $e(i)$ is the error at iteration i , $a(i)$ is the network output at iteration i and $t(i)$ is the corresponding target vectors at iteration i . Cybenko (1989) and Hornik et al (1989) showed that a two layer MLP with sigmoid non-linearity could approximate any function with arbitrary accuracy (the property of universal approximation). The most desirable property of applying neural networks to pattern recognition problems is their ability to accurately generalise to new situations. Two main reasons can cause a bad network performance:

- An unsuitable and unrepresentative input feature: in this case either too many bad features are selected or the training features do not allow a good generalisation. For instance, the sample space may be incomplete i.e. samples needed for an adequate training of the network are simply missing. A good feature pre-processing method should prevent this situation occurring
- An inadequate network configuration: This refers to the process of selecting the network architecture (mainly the number of neurons in the hidden layer and the training algorithm), and depends on the complexity of the underlying function, which the MLP is attempting to approximate.

2.4.4.2 Selecting Neural Network Architecture

The network architecture should allow for an adequate description of the underlying statistical distribution of the spread in the data. Since the number of inputs (input features) and the number of neurons in the output layer is fixed in many applications, the main concern is with the number of hidden layers and the number of neurons therein.

It was mentioned earlier that a two layer MLP with sigmoid non-linearity can approximate any function with arbitrary accuracy, and this therefore reduces the problem of defining the network architecture to one of choosing the number of hidden neurons. Choosing the number of hidden neurons depends on the complexity of the underlying function, which the MLP is attempting to approximate. Too many hidden neurons and the danger exists that the training set is simply memorised. Similarly a MLP with too few hidden neurons will not generalise well to new data sets.

2.4.4.3 Neural Network Training Algorithms

In terms of training algorithms for MLP, the neural computing literature is full of papers describing different algorithms, all of which adjust the weights of the network iteratively to minimise the network *performance function*. All of the training algorithms use the gradient of the performance function to determine how to adjust the weights to minimise performance, using the backpropagation techniques, which involves performing computations backwards through the network.

The most basic of these backpropagation algorithms is the gradient descent algorithm, which updates the network weights and biases in the direction in which the performance function decreases most rapidly- the negative of the gradient. However a problem with this algorithm is that the network can easily become trapped in a local minimum instead of attaining the sought-for global one. In that case even the training set cannot be fit properly. To circumvent this problem the steepest descent with momentum technique is

usually used. This involves making weight changes equal to the sum of a fraction of the last weight change and the new change suggested by the backpropagation rule.

The magnitude of the effect that the last weight change is allowed to have is mediated by a momentum constant (mc), which can be any number between 0 and 1. When the momentum constant is equal to 0, a weight change is based solely on the gradient, while if the momentum constant is equal to 1, the new weight change is set equal to the last weight change and the gradient is simply ignored. The gradient is computed by summing the gradients calculated at each training example, and the weights and biases are only updated after all training examples have been presented (batch training). Therefore the momentum allows a network to ignore small features in the error surface and not to become stuck in a shallow local minimum. If the new performance function on a given iteration exceeds the performance function on a previous iteration by more than a predefined ratio, the new weights and biases are discarded, and the momentum coefficient is set to zero.

Gradient descent, even with the inclusion of a momentum term, is not necessarily a very efficient algorithm for minimizing the performance function and is often too slow for practical problems. To overcome this limitation several high performance optimisation algorithms that can converge from ten to one hundred times faster than the gradient descent algorithms have been introduced, Hagan et al (1996). These optimisation algorithms fall into two main categories. The first category uses heuristic techniques, which were developed from an analysis of the performance function. The second category uses standard numerical optimisation techniques for neural network training. These are summarized in the table below. The derivation of these algorithms and their relative merits are discussed in detail by Hagan et al (1996). The naming and acronyms of these algorithms are also adopted from Hagan et al (1996).

Table 2.2: Training Algorithms for MLP

Acronym	Algorithm	Optimisation Approach
GDM	Gradient Descent with Momentum	Modification to Backpropagation (slow for practical applications)
GDX	Variable Learning Rate	Modification to Backpropagation
RP	Resilient Backpropagation	Modification to Backpropagation
SCG	Scaled Conjugate Gradient	Numerical Optimisation Technique
CGB	Conjugate Gradient with Powell/Beale Restarts	Numerical Optimisation Technique
CGF	Fletcher-Powell Conjugate Gradient	Numerical Optimisation Technique
CGP	Polak-Ribiere Conjugate Gradient	Numerical Optimisation Technique
OSS	One-Step Secant	Numerical Optimisation Technique
LM	Levenberg-Marquardt	Numerical Optimisation Technique
BFGS	Quasi-Newton	Numerical Optimisation Technique

The criterion for deciding when to terminate training in the above algorithms is one of the main contributors to bad generalisation (overfitting). The training is usually stopped when a local minimum is attained or when the convergence rate has become very small, i.e. improvement of iteration to iteration is zero or minimal or simply when a certain number of epochs (cycles) is reached. However this leads to overfitting, i.e. memorisation of the training set: now the noise is fitted, not the global trend. Hence the obtained weight distribution will be optimal for the training samples, but it will result in bad performance in general.

Different types of techniques have been introduced to improve generalisation to avoid the overfitting problem. Two of the widely used methods are cross-validation, otherwise known as early stopping and Bayesian regularisation.

2.4.4.4 Cross-Validation

The cross validation technique divides the available data into three subsets. The first subset is the training set, which is used for computing the gradient and updating the network weights and biases. The second subset is the validation set. The error on the validation set is monitored during the training process. The validation error will normally

decrease during the initial phase of the training set error. However, when the network begins to overfit the data, the error on the validation will typically begin to rise. When the validation error increases for a specified number of iterations (epochs), the training is stopped, and the weights and biases at the minimum of the validation error are returned. The third subset is the test set, which is removed before any training is done, and which is not used again until all training is done. The error on the test set is used to test the model generalisation ability.

Although the cross-validation technique generally produces good results, it results in a reduced training set that may pose a problem if a limited number of data is available. Due to the fact that only part of the available data is used to train the model and also since training is stopped before a minimum of the training error, the effective number of parameters remains less than the number of available parameters, the information contained in the selected samples is not optimally used and the risk of under-constrained training increases.

2.4.4.5 Bayesian MLP Neural Network (Regularisation)

Another method of improving generalisation is using Bayesian MLP Neural Network, otherwise known as Bayesian Regularisation. Bayesian methods use probability to quantify uncertainty in inferences and the result of Bayesian learning is a probability distribution expressing our beliefs regarding how likely the different predictions are. A practical problem with MLPs is in controlling the complexity of the model (i.e. how to select the right number of neurons in the hidden layer and control the weights and biases of the network). The Bayesian approach offers efficient tools for avoiding overfitting and have become a viable alternative to the older error minimisation based approaches, Mackey (1992) and Bishop (1995a). In this method the performance function is complimented with additional terms that consists of the mean of the sum of squares of the network weights and biases as follows:

$$F = \beta E_D + \alpha E_w \quad (2.36)$$

Where α and β are the objective function parameters, E_D is the performance function and E_w is the sum of squares of the network weights as defined below.

$$E_w = \frac{1}{2} \sum_{j=1}^n w^2_j \quad (2.37)$$

Using the modified performance function of Eqn. (2.36) will cause the network to have smaller weights and biases, and this will force the network response to be smoother and less likely to overfit. The problem with regularisation is that it is difficult to determine the optimum value for the performance ratio parameter. If we make this parameter too large, we may get overfitting, and if the ratio is too small, the network will not adequately fit the training data. One solution to this problem is the Bayesian framework as suggested by Mackey (1992). In this framework, the weights and biases of the network are assumed to be random variables with specified distribution. The regularisation parameters are related to the unknown variances associated with these distributions. Statistical techniques are then used to estimate these parameters. A detailed discussion of the use of Bayesian regularisation, in combination with the Levenberg-Marquardt training algorithm is given by Foresee et al (1997), but the main steps needed to implement this algorithm are summarised below.

1. Initialise α and β and the weights.
2. Take one step of the Levenberg-Marquardt training algorithm to minimise the objective function. $F(w) = \beta E_D + \alpha E_w$ (2.38).
3. Compute the effective number of parameters, $\gamma = N - 2\alpha \text{tr}(H)^{-1}$ (2.39) using the Gauss-Newton approximation to the Hessian matrix available in the Levenberg-Marquardt training algorithm. Where N is the total number of parameters in the network and H is the Hessian matrix. γ is a measure of how many parameters in the neural network are effectively being used in reducing the error function and it can range from 0 to N .
4. Compute new estimates for the objective function parameters

$$\alpha = \frac{\gamma}{2E_D(w)} \quad (2.40)$$

$$\text{and } \beta = \frac{n-\gamma}{2E_D(w)} \quad (2.41).$$

5. Now iterate steps 2 through 4 until convergence

The following factors should be checked during training for model performance

- If γ is very close to N , then the network may be too small. Add more hidden layer neurons and retrain.
- If the larger network has the same final γ then the smaller network was large enough.
- Otherwise increase the number of hidden neurons
- If a network is sufficiently large, then a larger network will achieve compatible values for γ , E_D and E_w .

The benefits of a regularisation technique together with the Bayesian Framework are summarized below.

- Regularisation improves generalisation
- Bayesian Framework provides a measure of how many network parameters (weights and biases) are being effectively used by the network
- Bayesian Framework eliminates the guesswork required in determining the optimum number of hidden neurons and consistently leads to good networks that are not over-trained (see chapter 5 for results obtained with this algorithm).
- Hessian matrix calculation is required
- Gauss-Newton approximation can be used to approximate the Hessian matrix
- Computational overhead is minimal when using Levenberg-Marquardt training algorithm, as it is 10 to 100 times faster than other training algorithms.
- If either sum of square weights or total number of effective parameters become the same two successive epochs, training may be terminated

- Applications to practical problems demonstrate feasibility (see Mackey (1992), also see results of current research in chapter 5.

Based on the literature surveyed, the current research study is the first reported work to apply Bayesian MLP neural network in an application involving multiphase flow measurement.

2.4.5 Application of PR Techniques to Multiphase Flow Metering

Some of the foregoing techniques of feature extraction and pattern recognition techniques have been applied to the area of multiphase flow measurement, and below some of the most relevant published literature will be reviewed.

The most prominent of the literature dealing with multiphase flow measurements using pattern recognition techniques is perhaps that conducted by successive researchers at Imperial College, London. This concept was first proposed by Darwich (1989). Here it was suggested that if the turbulence characteristics of multiphase flow conditions are reproducible, then the flow rates of individual phases can be determined by identification of these characteristics. Using this approach a set of features were derived from the turbulent pressure signals and pattern recognition methods were used for the identification and measurement of the individual phase flow rates in two-phase flow. A statistical technique known as template matching was used as the pattern classifier model. A software package called ESMER was built as a result.

Darwich (1989) used absolute pressure transducers and differential pressure transducers mounted radially and axially, capacitance and conductance sensors to collect data in two-phase (air-water) flow in horizontal 2-inch loop. In terms of feature extraction all together 8 features were found to be effective. These were, three amplitude domain features (SD, CS, and CK) and five linear prediction coefficients.

All of the eight features were extracted from the pressure signals but only three were effectively extracted from conductance and capacitance sensors (SD, CS, and CK). A statistical pattern recognition technique known as template matching was used as the pattern recognition model. Flowrates were identified by matching the measured feature vectors to those in the calibration database. Measurement accuracy of $\pm 10\%$ was achieved for 90 % of the data tested.

Toral et al (1990) used an orifice plate in two-phase flow (air-water) to study its effect on feature generation. It was found that the discriminating strengths of features were enhanced by the presence of the orifice plate. Beg and Toral (1993) studied pipeline installation effects on the measurement techniques and proposed that the upstream disturbances and pipeline geometry can be isolated by means of a homogeniser, which could lead to an off-site calibration.

Beg et al (1993) applied MLP neural networks for the measurement of oil-water-air. They used gamma ray densitometer, pressure, conductance and capacitance sensors to predict flow regimes and individual phase flow rates in 3-inch and 16-inch diameter multiphase pipelines. For both gamma and pressure sensors 24 feature vectors were extracted from the time series. These were mean, variance, minimum and maximum and 20-bin amplitude histogram of the sensor measurement history. Accuracies of $\pm 10\%$ were obtained from gamma ray densitometer and $\pm 18\%$ from pressure sensor measurements were achieved on gas and liquid flow rates. The cross-validation technique was used to improve generalisation.

Bishop and James (1993) and Bishop (1995b) proposed a method of analysing multiphase flows using dual-energy gamma densitometry and MLP neural networks. This study was based on the use of three vertical and three horizontal gamma densitometer beam lines installed in parallel across the pipe. Four different flow configurations were considered (homogeneous, stratified, annular and inverse-annular). The input features to the network were 12 path lengths measured by the gamma densitometer beams for the four different flow configurations. The volume fractions of oil and water phases were used as the target

vectors. The numerical optimisation technique known as the Quasi-Newton (BFGS) was used as the training algorithm, see Table (2.2). A network having a various number of hidden units was trained, each for 300 complete epochs (cycles) of the BFGS optimisation algorithm. It was shown that a neural network technique could provide a practical solution to the problem of extracting phase fractions from gamma densitometer data.

Akartuna (1994) conducted experiments in air-water and oil-air-water flows with strip type capacitance sensors together with pressure sensors in a horizontal 2-inch flow loop. Similar features to those used by Darwich (1989) were used here with the addition of two new features, “slug frequency” and “slug length”. Template matching and MLP neural network with GDM training algorithm techniques were applied to the reproducibility of individual phase flow rates. Of the two techniques, the neural network was shown to give better results when combinations of pressure and capacitance signals were used. In terms of measurement accuracy, 97 % of watercut, 90 % of air velocity and 90 % of liquid velocity samples were measured to within ± 10 % tolerance.

Cai (1995) also used pressure and capacitance sensors in oil-water-air flows in horizontal 2-inch flow loop. The same features as those used by Akartuna (1994) were used with the use of the F-ratio and feature saliency criteria for feature selection. MLP neural network was used for the identification of flow rates. In watercut measurements, 100 % of oil continuous samples and 95.2 % of water continuous samples were identified to within ± 5 % error band. In superficial velocity measurements, 99.3 % of the air superficial velocity and 100 % of the liquid velocity were measured to within ± 9 % error band.

Beg (1998) extended the work of Darwich (1989) and used absolute and differential pressure transducers configured radially and axially in a 2, 3 and 4-inch horizontal flow loop. In this study a new set of features were extracted, two in amplitude domain (AV, CV) and five in the Cepstrum domain. The template matching technique was used as the pattern recognition method. The measurement accuracy reached 100 % for the liquid

phase and up to 93 % for the gas phase (i.e. measured to within ± 10 % relative error), when combinations of different features were used. The 3-inch and 4-inch feature distribution maps were also compared and it was noticed that they exhibited different turbulence signatures under the same inlet flow conditions. As a result it was suggested that each pipeline should have associated calibration data if an acceptable level of flow measurement accuracy is to be achieved. This led to the investigation of possible scaling from one pipe to another. It was shown that scaling is feasible provided that a proper selection of hydrodynamic coordinate systems and feature vectors were employed. The measuring accuracy determined, however was found to be lower than that achieved with *in-situ* calibration.

In 1992, the ESMER pattern recognition technique that was originally suggested by Darwich (1989) became commercialised by Petroleum Software Limited (PSL). The metering system comprises a non-intrusive pipe of 2 m length and 4-inch diameter fitted with three differential pressure sensors (a top axial DP, bottom axial DP and radially mounted DP sensors), impedance sensors (capacitance and conductance sensors mounted axially on top) and a resistance temperature detector (RTD). Stochastic features are extracted from these sensors and a MLP neural network model with cross-validation algorithm is used for classification of flow rates, Toral et al (1999). The database is divided into three parts, a training set which the neural network is calibrated, a validation set to prevent overfitting and testing to check the meters generalisation performance, Toral et al (1999) and Wood (2003). The system measured the gas and liquid flow rates to within ± 10 -15 % relative bases on results obtained at Auk platform, Toral et al (1998). The focus to date has been on the liquid continuous applications of multiphase flow metering with no applications reported on wet gas flow applications.

Goudinakis et al (2003) applied a MLP neural network for flow regime identification in a horizontal pipeline and S-shaped riser for two-phase (air-water) flow. The flow regimes considered were Stratified Smooth (SS), Stratified Wavy (SW), Bubble flow and Slug flow. They used a capacitance sensor for horizontal system and two pressure transducers for the S-shaped riser. The raw data in time series format (a fixed length analysis

window at a time) were used as input to the classification model. Supervised MLP neural network with the target outputs equal to the number of flow regimes required to be identified was used as the classification model. It was found that a delay window of 200 inputs for a horizontal pipe and 100 inputs of data for the S-shaped riser was sufficient for the task of flow regime classification.

Although this technique was seen as a useful methodology for on-line monitoring of dynamic systems, a drawback of this methodology was also identified, as being the long training time required to providing classifications, which may make such a technique too slow for practical applications.

2.4.6 Performance Appraisal

In order to get a quantitative analysis of the pattern recognition results, different appraisal criteria are usually applied to the pattern classifier output. The following techniques are usually used to appraise the pattern recognition performance.

The relative error can be calculated between the target vectors and the pattern recognition model outputs. This technique was used amongst others by Darwich (1989), Akartuna (1994), Cai (1995) and Beg (1998) to describe the measuring accuracies of their respective flow measurement results. This is computed as follows: -

$$E_r = \frac{Q_{(predicted)i} - Q_{(measured)i}}{Q_{(max)} - Q_{(min)}} \times 100 \quad (2.42)$$

Where: -

Q is the gas or liquid flow rate

$Q_{(max)} - Q_{(min)}$ is the difference between maximum and minimum flow rates (i.e. measurable flow range).

Another approach is to calculate the Root Mean Square Fractional Deviation (d), which is a measure of the standard deviation between the observed and the predicted values.

$$d = \sqrt{\frac{1}{N} \sum_{i=1}^N \left(\frac{Q_{(predicted)i} - Q_{(measured)i}}{Q_{(measured)i}} \right)^2} \quad (2.43)$$

Smith and Leang (1977) and Steven (2001) amongst others used this criterion in their studies of flow correlation comparisons.

A third approach is to calculate the correlation coefficient; R, which is a measure of the linear relationship between the values for the two variables, Johnson (1994).

$$R = \frac{S_{xy}}{\sqrt{S_{xx}S_{yy}}} \quad (2.44)$$

$$S_{yy} = \sigma_y^2 (N-1) \quad (2.45)$$

Where σ_y is the sample sigma (i.e. the standard deviation of the samples drawn from the y values). S_{xy} and S_{xx} are the regression function parameters used to calculate the slope and the intercept and N is the total number of observations. The correlation coefficient can range between +1 and -1. Positive values indicate a relationship between X and Y variables so that as X increases so does Y. Negative values mean the relationship between X and Y is such that as values for X increase, values for Y decrease. A value near zero means that there is a random, non-linear relationship between the two variables.

2.4.7 Platform for Neural Network Implementation

There are currently many neural network software packages available including both commercial packages and public domain software. These packages range from simple demonstration of introductory software to large commercial packages supporting a range of network architecture and training algorithms. Many of the commercial packages interface with standard spreadsheets, from which they obtain their input data. This provides a flexible environment for designing, training and testing the neural network without requiring a heavy investment in software development. An example of such software, which is used in this research, is MATLAB from MathWorks.

An added advantage of MATLAB is that it is an integrated technical computing environment that combines data acquisition, signal processing, statistical techniques, neural networks, high level of programming language, and many more functionalities. The open architecture makes it easy to use MATLAB and companion products to explore data and create custom tools that provide early insights and competitive advantages. The version of MATLAB that was used in this work was 6.0.0.88, Release 12, September 22, 2000.

Appendix A contains the programs written from data acquisition, signal processing, feature extraction and selection and neural network models used in this research using MATLAB's programming language.

This chapter has covered the literature cited on the measurement of wet gas flow, including techniques that are still in the development stage, like dry gas flow meters as well as mature methodologies and commercially available techniques. The chapter has also highlighted the technical challenges that are facing these measurement techniques when they are applied to wet gas flow. The second part of this chapter covered the approach of pattern recognition techniques, which is the approach this research is taking for wet gas flow measurements. The following chapter will therefore detail the experimental set-up and data acquisition system performed for the current research work.

CHAPTER 3

EXPERIMENTAL SET UP AND DATA ACQUISITION

This chapter describes the experimental facility used to obtain wet gas and multiphase flow information, together with test equipment and sensors and including the procedure developed for data acquisition.

3.1 Test Rig and Flow Supply Lines

All tests of this work were performed at the multiphase flow laboratory (HANGAR 1) of Cranfield University, Cranfield. The test rig is a once through air-water flow system. The majority of the test rig was constructed from galvanised steel pipes, however, various sections utilised flexible hoses, in order to minimise mechanical bends and to speed up the rig assembly.

As shown in Figure 3.1, the air is drawn into, and through, the test section using a positive displacement compressor, with a capacity of 400 f³/m (11.3 m³/m) at 18-barg. Pressure was regulated at 3 stages; at the compressor itself, at the inlet to the vertical air setting tank (air receiver) and finally at just upstream of the test section, where it could be regulated at the desired test pressure. At the outlet of the compressor the air is accumulated in the vertical receiver, which stabilises the flow and eliminates the load/unload effect of the compressor and thereby supplying constant flow of air to the test section. The air is then passed through a dryer to dehumidify and remove any other liquids such as compressor lubricating oil, before it is passed to the filter to remove any particulate. A clean, dry air is therefore supplied to the test section. The turbine meter, FM15, measures the airflow rate. The flow range of the FM14 turbine flow meter was too low for the high gas velocities required in wet gas testing, and it was therefore not utilised in the current work. The needle valve, V24 is used to fine-tune the required airflow rate.

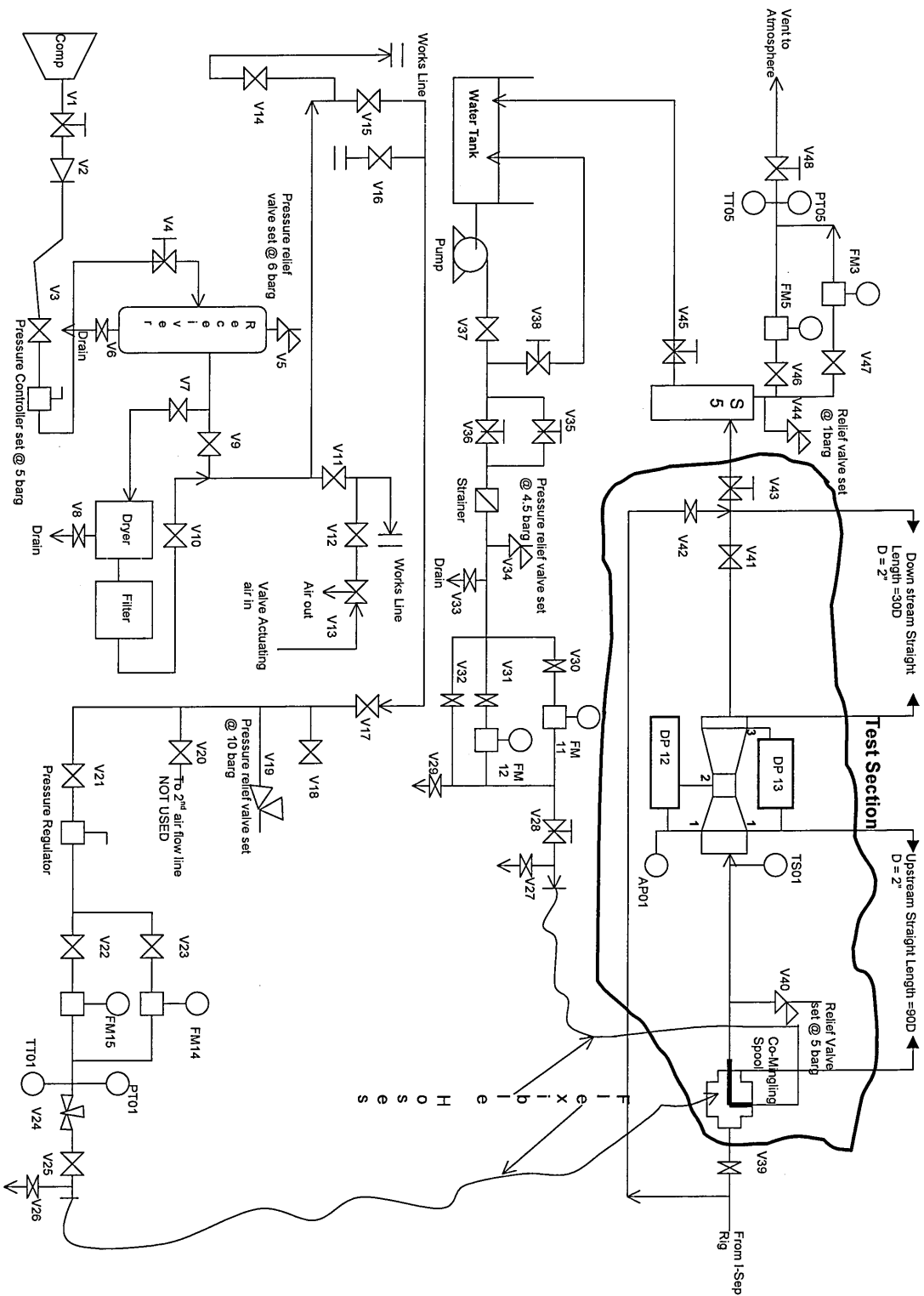
Water was supplied from the water tank by a two stage centrifugal pump with a design capacity of 7.4 l/s at 10.5 barg. The bypass line and valve 38 were used for regulating the water supply pressure. The flow rate could be set using valves V35 and V36, and is measured either by the turbine flow meters FM11 or FM12, depending on the required flow rate. Ball valves were used where an on/off function was required throughout the rig, but for flow control, gate or needle valves were used.

Once it had passed through the test section (described below), the two-phase air-water mixture was directed through a knockout drum (S-5), where the water in the flow was removed and directed back into the water tank and the air through one of two gas V-Cone flow meters, before it is vented to atmosphere. Although no calibration checks are usually required on turbine flow meters for the duration of one year since their factory calibration. The idea of having the V-Cone flow meters, together with the local pressure and temperature readings at the outlet of S-5, was to provide a total system mass balance of air and to check that the inlet gas turbine flow meter (FM14) was reading correctly. When this was done the inlet turbine meter and the V-Cone had an agreement with measurement error of $\pm 3\%$ relative to the turbine reading.

The water turbine flow meters were also checked periodically throughout the test period. This was done by choosing a flow rate, which is within the envelope of both meters operating range and comparing their readings. A measurement error of better than $\pm 1.5\%$ was calculated in this case between the two flow meters. Carrying out “tank measurements” made further verifications, where the water volume drained into the graduated separator (S-5) was measured with a stopwatch and then compared against both FM11 and FM12. When the latter calculations were done, a measurement accuracy of $\pm 1.8\%$ was obtained for FM11 and better than $\pm 3\%$ for FM12 based on the reference turbine meter readings.

The above measurement errors were consistent throughout the periodic verifications, and were therefore taken as an acceptance criterion for inlet turbine flow meter readings.

Figure 3.1: P&ID FOR VENTURI WET GAS METERING TESTS



Flow Meter (l/s) and Pressure Ranges

- FM3: (V-Cone 3/4") 0.62-6.24 @ 1barg
- FM5: (V-Cone 1 1/2") 2.49-49.99 @ 1barg
- FM11 (QFL 32): 0.55-5.55
- FM12 (QFL 13): 0.11-0.75
- FM14 (QFG16): 0.41-4.1
- FM15 (QFG50): 4.1-69.4
- DP12: 350 mbar with $\pm 0.04\%$ FSD
- DP13: 175 mbar with $\pm 0.08\%$ FSD
- AP01: 2 bar with 0.1 % FSD

SCALE: NOT TO SCALE

DRAWN BY: A.A.J

DATE: 13 FEBRUARY, 2000

LEGEND

- Ball Valve
- Gate Valve
- Needle Valve
- Pressure Relief Valve
- Flow Meter
- Venturi Meter

3.2 Venturi Meter Design

The Venturi meter was designed in accordance with British Standard, BS 1042 and International Standard ISO 5167. The Shell Flow Meter Engineering Handbook by Danen (1985) also gives practical design calculations.

Table 3.1 below shows the fluid physical properties and maximum design conditions used while designing the meter. Where ρ and μ are the density and viscosity with the subscript g and l signifying gas and liquid respectively. Based on the desired test matrix (see section 3.5), the maximum design gas flow rate was 252 cubic meters per hour and the maximum design liquid flow rate was assumed to be 7.2 cubic meters per hour. The meter was designed for gas volume fraction (GVF) of 95% and maximum differential pressure across the Venturi throat of 300 mbar.

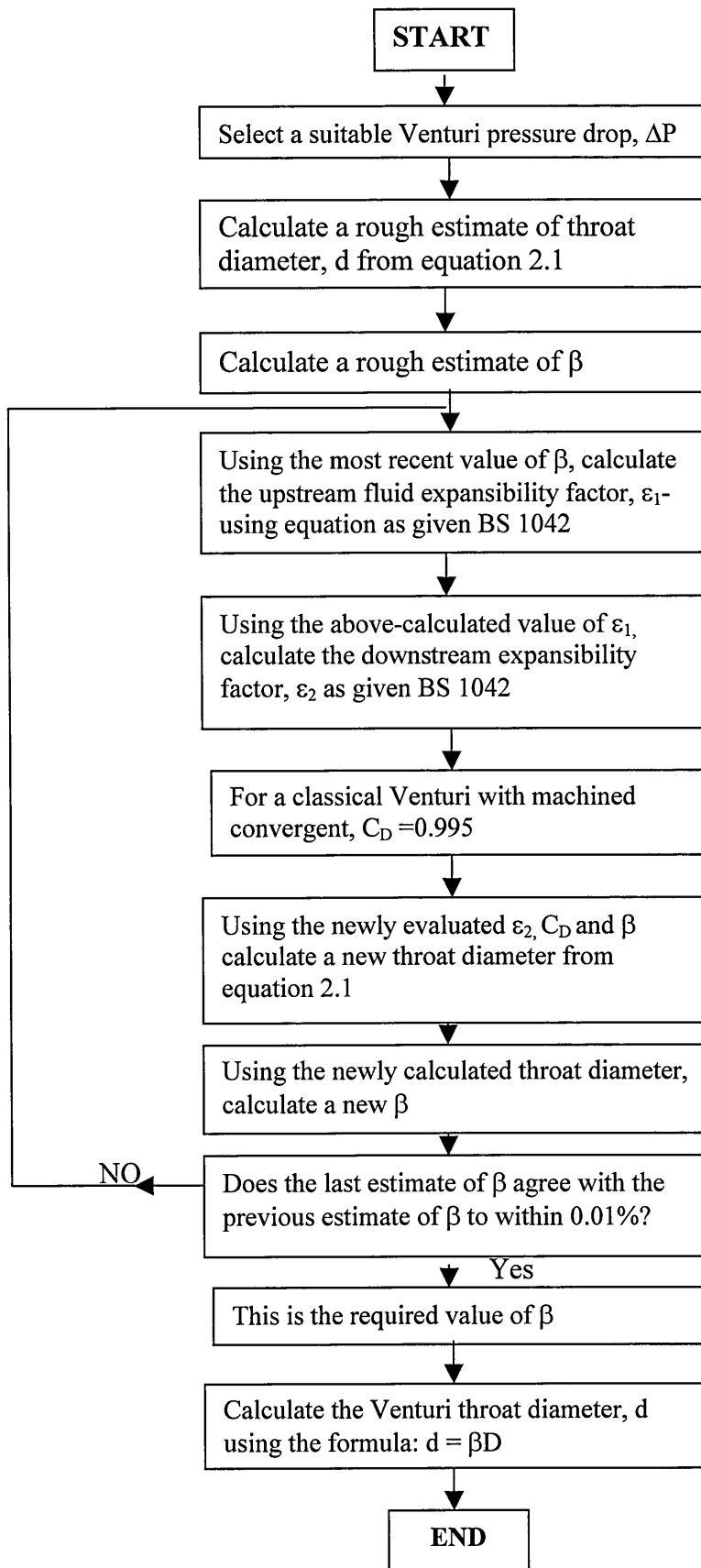
Using the classical Venturi equations, as contained in the above standards, a simple iterative procedure was developed in order to devise the Venturi size that would satisfy the required design conditions.

A classical Venturi meter having a beta ratio, $\beta = 0.74$ and throat diameter 1.48 inches was found to satisfy the required design conditions. The dimensions of this meter are given in Figure 3.3.

Table 3.1: Design Parameters at near Atmospheric Conditions

ρ_g	ρ_l	μ_g	μ_l	Q_{gmax}	Q_{lmax}	GVF	Max DP
kg/m ³	kg/m ³	Ns/ m ²	Ns/ m ²	m ³ /h	m ³ /h	%	mbar
1.29	1000	1.8x10 ⁻⁵	1.0x10 ⁻³	252	7.2	95	300

Figure 3.2: Flow Chart for Throat Diameter Calculation



3.3 Venturi Calibration

The discharge coefficient of 0.995, which is given by the ISO 5167 for classical Venturi meters is only applicable to single-phase, Newtonian fluids having Reynolds numbers in the range between $2 \times 10^5 \leq R_{ed} \leq 1 \times 10^6$, where the C_D is believed to become independent of Reynolds number and remain at 0.995. However in the current research work, the available pump could only deliver 7.5 l/s at 10.5 bar, which corresponds to a R_{ed} of approximately 60×10^3 at the test section. Similarly, the compressor's maximum safe working pressure limited the delivery to a R_{ed} of about 178×10^3 at the test section.

The above rig limitations meant that the Venturi meter was operating outside the standard's coverage and therefore had to be calibrated with the current conditions to obtain discharge coefficients for air and water, which are characteristic of the current Venturi meter. These values will be required for use with empirical correlations in chapter 6. The usual calibration curves of discharge coefficient versus Reynolds number for air are given in Figures 3.4a and 3.4b, with an average discharge coefficient of 0.989. Figures 3.6a and 3.6b display the results of Venturi calibration with water, giving a lower average discharge coefficient of 0.980 due to Reynolds number being lower in water flow than air as a result of lower velocities.

The gas and liquid reference flow rates were measured using traceable, calibrated, reference turbine flow meters, provided by Quadrina Ltd.

Figure 3.4: Venturi Calibration with Air

Figure 3.4a: Variation of CD with Reynolds Number

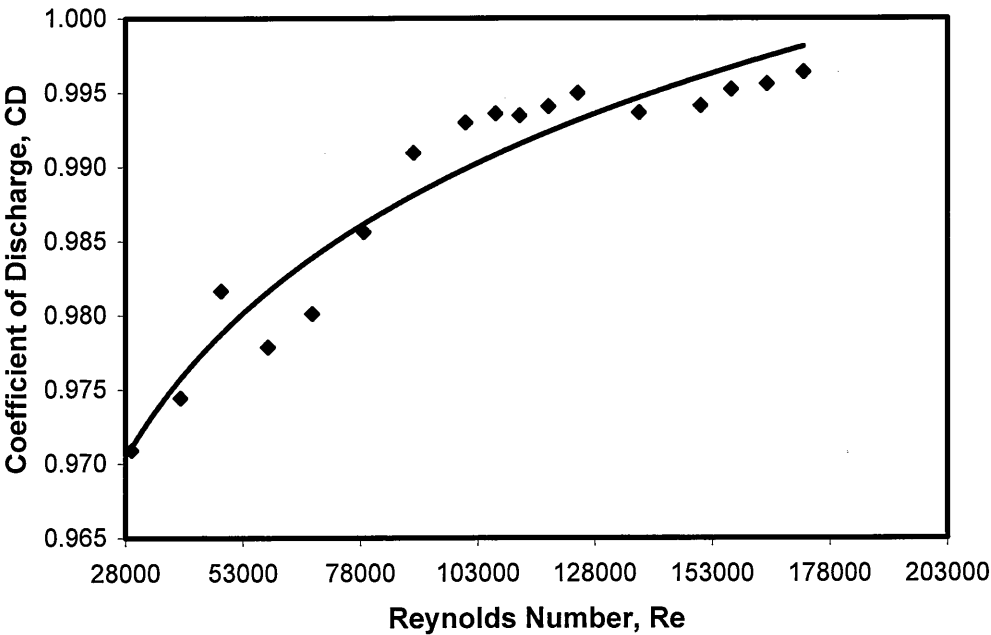


Figure 3.4b: Venturi Calibration with Air

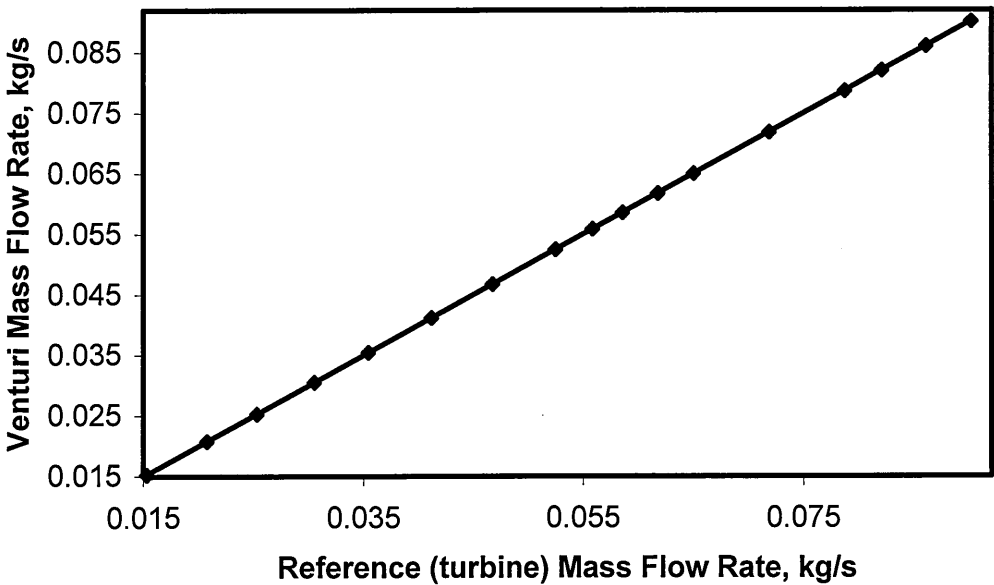
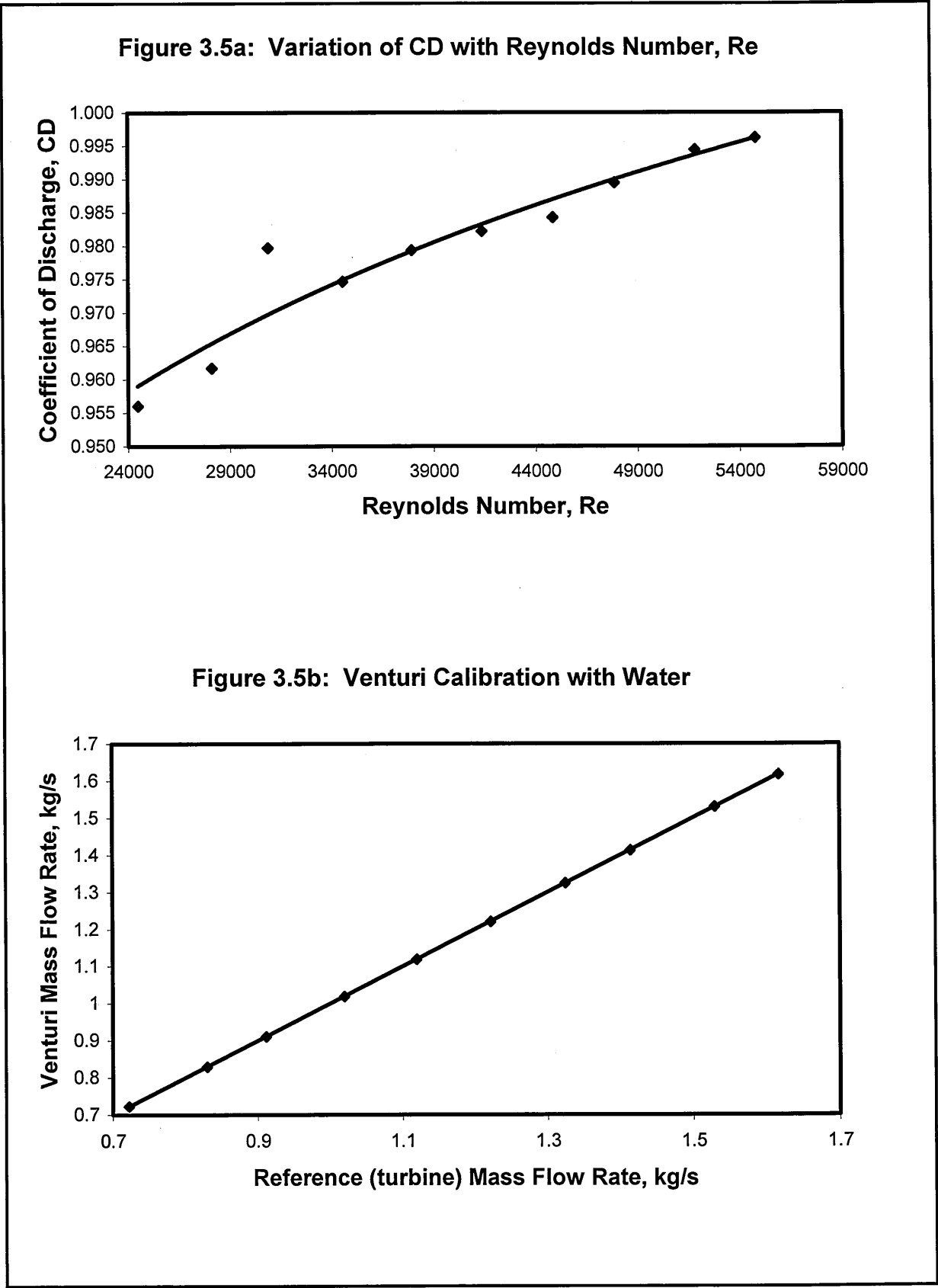


Figure 3.5: Venturi Calibration with Water



3.4 Test Section

Typically, multiphase flow meters may be arranged in a vertical or a horizontal flow configuration. Most multiphase flow meters utilising Venturi meters are arranged with a vertical upward flow through the Venturi meter preceded by a blind-tee. This is because vertical installation minimises stratification, which is necessary for the assumption of homogeneous condition. The present study is not based on homogeneous assumption but is founded on the premise that the turbulence characteristics of multiphase flow are uniquely related to the flow rates of the individual phases in a given set of conditions, hence the Venturi meter was mounted horizontally, as this orientation would result with the greatest discriminate signature (slip) between the phases.

The Venturi tapping lines (impulse lines) were always filled with water. This was achieved by installing purge valves at either side of the impulse lines and before each test run they were filled with water, and the air was evacuated through the valves. After the lines were filled with water and before the start of the test run, the hydrostatic pressure differential at static conditions in the impulse lines was equated to zero pressure.

A classical Venturi meter with a β ratio of 0.74 was subjected to two-phase flow consisting of air and water. The Venturi run was installed horizontally on the test section consisting of 12 m length and 50.8 mm (2 inch) inside diameter, constructed of clear acrylic Perspex. This enabled observation of the flow regime upstream and downstream of the Venturi meter.

The water was introduced into the airflow stream path through a concentric tube in the centre of the cross-commingling spool with 12.7 mm diameter. The tube extended out into the radius of the pipe cross-section and made a 90° bend to point downstream aligned with the centre of the pipe for a length of 0.1m. The purpose of this set up was to create a fully developed (steady state) annular flow regime, with a gas core in the centre of the pipe and liquid annular films adjacent to the pipe wall. Initially, a spray nozzle head was attached to the end of concentric tube to enhance the establishment of a fully

developed annular/mist flow through the Venturi, but it was noticed that the spray head induced significant pressure drops, especially when higher liquid loading was required. Further tests showed that a fully developed, annular mist flow regime could be established without the use of the spray nozzle, verified by visual observations. The spray nozzle was subsequently removed, and water introduced through the concentric tube.

The measurement accuracy of a flow meter can be effected by upstream disturbances in the flow in the form of bends, wellhead choke, pipe diameter changes, etc. These disturbances generate swirls and may change the flow regime in the flowing stream. There is no consensus in the open literature regarding the development length required after the two-phases are introduced to each other. Some workers have tested meters in fully developed flow regimes, the settling length required is dependent on the developed flow regime, slug flow requiring the greatest length, stratified flow the least. All descriptions of two-phase flow test apparatus simply state the location of the commingling spool-piece relative to the test section. The upstream development length reported for Venturi meters operating in two-phase flow in horizontal pipelines conform to the range of 38-70D (e.g. Collins and Gacesa 1971, Roberts 1997, de Leeuw 1997, Lund and Tait 1999, Steven 2000, Stewart 2002). In this work, 90D upstream straight length was provided to ensure a fully developed flow (i.e. steady state) for two-phase flow and 30D downstream straight length.

The determination of fully developed flow regime in this work was made on number of criterions including visual observation of the particular flow regime, which was confirmed by observing the flow through the 90D clear acrylic Perspex upstream section, ensuring that the gas and liquid inlet flow rates were at steady state and pressure and temperature stable and that the differential pressure readings of the Venturi meter were also at steady state (i.e. DP12 and DP13 would stay relatively constant for each set of gas and liquid flow rates). However, the present technique is founded on the premise that the turbulence characteristics of multiphase flow are uniquely related to the flow rates of the individual phases in a given pipe under a given set of conditions and hence it may be

possible that the accuracy of the current proposed technique for wet gas metering is rig dependent as indeed are most multiphase meters. Chapter 5 investigates two such rig influences (flow regime change and pipeline operating pressure).

Figure 3.3 details the shape and dimensions of the Venturi meter used for the current work. The Venturi meter was made by machining a solid cylindrical block of acrylic Perspex for flow visualisation purposes, and its dimensions conformed to those specified by the ISO 5167 for classical Venturi tube with machined convergent section.

The differential pressure sensors were high precision sensors, supplied by Druck Limited. The principal of operation is that of strain gauge with Wheatstone bridge configuration. In addition to the pressure range given in Table 3.1, these differential pressure sensors have an allowance for over pressurising of up to 4 times the range given without affecting their accuracy or causing physical damage. The accuracies quoted below are from the best-fit straight line including the effects of non-linearity, hysteresis and repeatability. DP12 measures the differential pressure between the upstream pressure and the throat tapping, which is the tapping positions covered by ISO 5167 for flow rate calculations.

Table 3.2: Pressure Sensor Specifications

Sensor	Manufacturer	Type	Pressure Range	Frequency Response	Principle of operation	Accuracy (%)
AP01	Data Instruments	SA	2 bar	1 kHz	Strain Gauge	± 0.1 FSD
DP12	Druck Limited	PDCR	350 mbar	2 kHz	Strain Gauge	± 0.04 FSD
DP13	Druck Limited	PDCR	175 mbar	2 kHz	Strain Gauge	± 0.08 FSD

The location of DP13 is not covered by the standard, and is introduced in this work to measure the pressure drop across the top position of the Venturi recovery length. The upstream position of DP13 is directly opposite the upstream position of DP12, and its downstream position extends 28mm after the Venturi conical divergence section. AP01 measure the absolute pressure at the Venturi upstream condition with TS01 measuring the corresponding line temperature. As showed in Figure 3.3, there are two taps, which are

not drilled through. These were intentionally left blind, so that if extra pressure sensors are required after the first phase of data analysis, these holes could be easily drilled without the need of demounting the test section.

3.5 Sampling Frequency

As discussed in chapter 2, the sampling frequency is a crucial step in the process of collecting meaningful data and to avoid aliasing.

As a starting benchmark, a storage oscilloscope was used to visualise the frequency of the pressure sensors at various test conditions. This showed that the maximum frequency in all the flow regimes was about 12 Hz, ± 2 Hz. To confirm this observation, data was collected at various sampling frequencies across the test matrix. Figures 3.6a to 3.6d display the results obtained for 20, 40, 80 and 160 Hz sampling frequency in the annular mist flow regime, using DP12 signals by way of example. The superficial gas and liquid velocities were kept constant at 36 and 0.1 m/s respectively. It is clear from the frequency spectrum that the significant information from the signal tends to concentrate at low frequencies (below 10 Hz), as indicated by the increase in the magnitude of the energy in this range.

Similar analyses were also carried out in the slug flow regime as shown in Figures 3.7a to 3.7d. It is also true of the slug flow regime that most of the signal energy is concentrated in the region below frequency of 10 Hz.

According to the sampling theorem, the Nyquist frequency is considered to be equal to 10 Hz. However, in order to capture not only the frequency but also the amplitude domain variations, the sampling frequency was selected to be five times the Nyquist frequency at 50 Hz with a sampling period 60 seconds (3251 points).

Figure 3.6: Sampling Frequency in Annular Mist Flow Regime

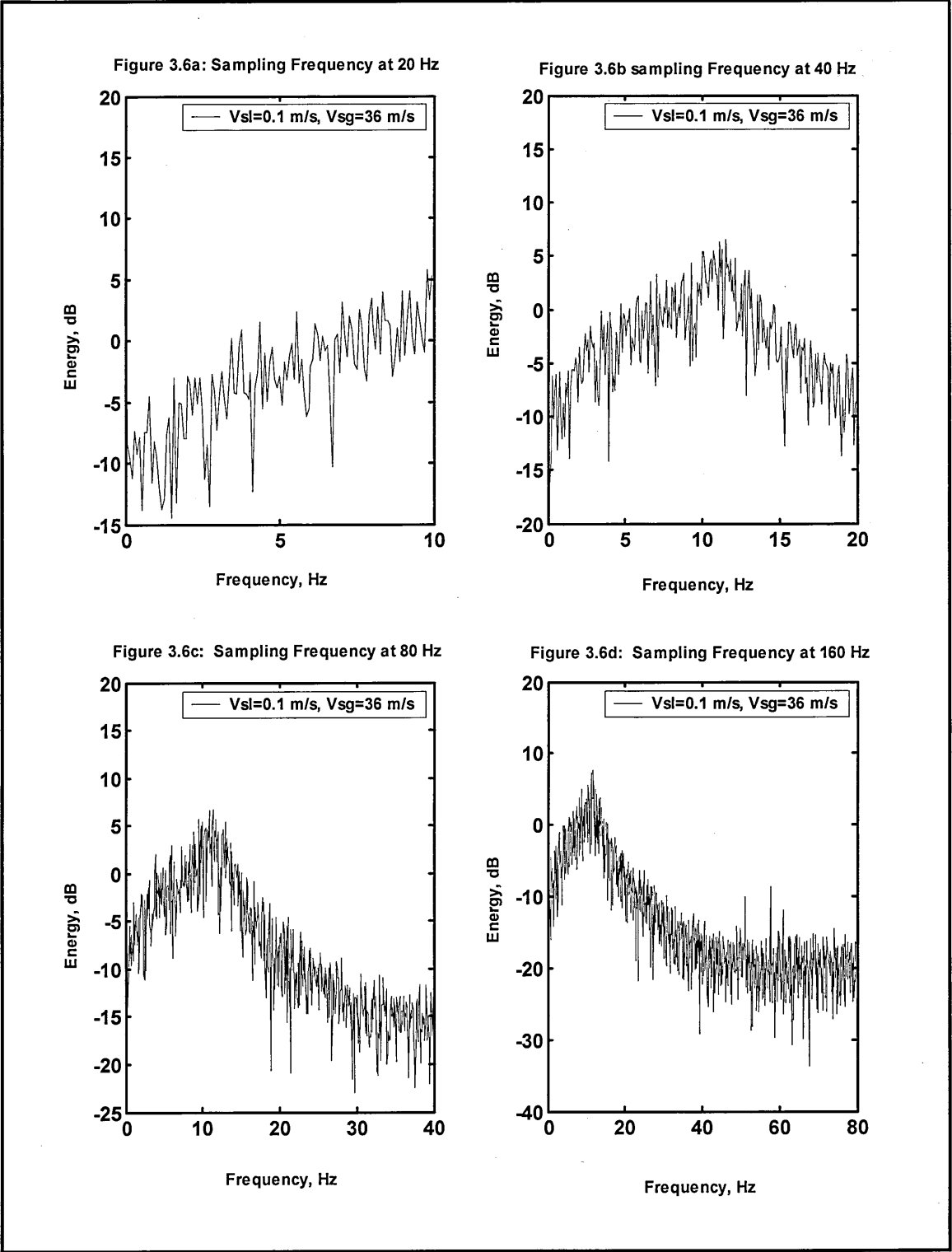
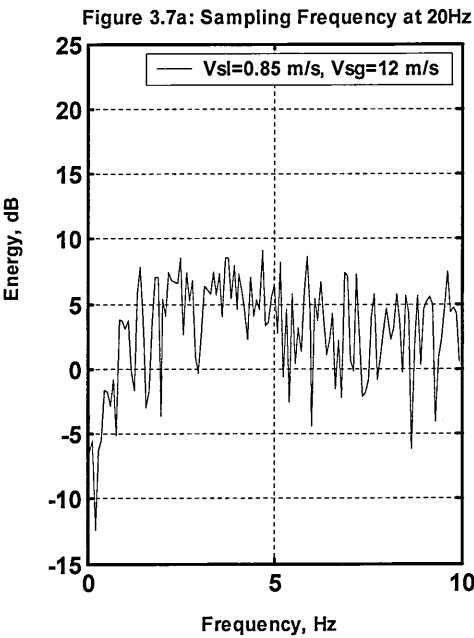
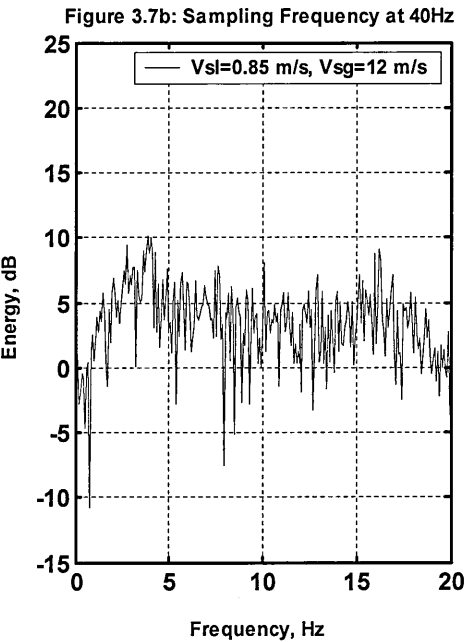
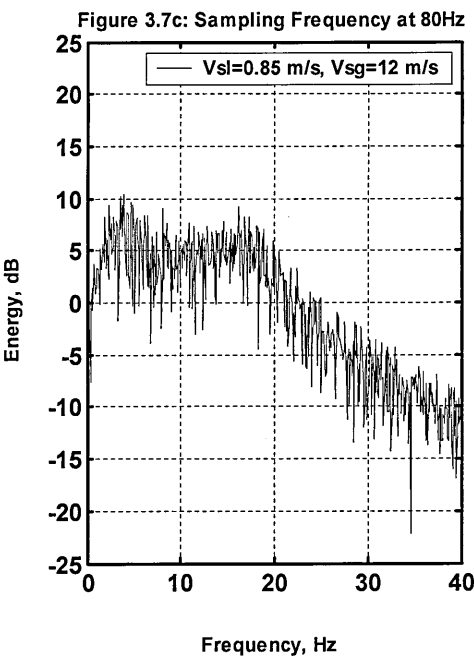
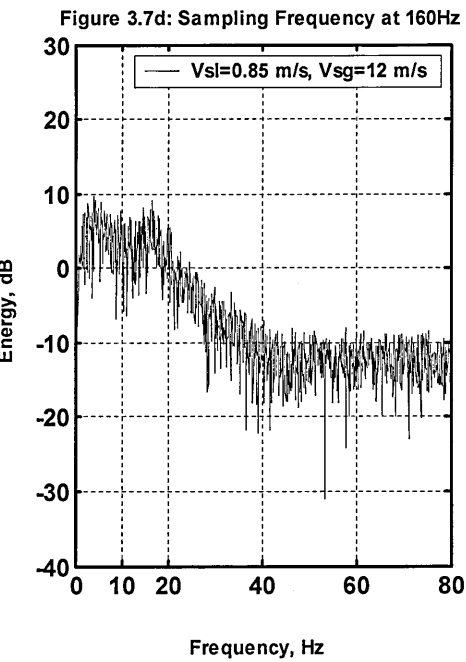


Figure 3.7: Sampling Frequency in Slug Flow Regime



3.6 The Data Acquisition System

The data acquisition system comprises an analogue-to-digital converter (ADC) card installed in a PC, together with a software program called LabView to drive the converter and carryout on-line processing of data.

The converter used was a 64 channel, 16-bit device (PCI 6031 E) manufactured by National Instruments. Although only 16 channels were monitored, the device was shared with another project so that either project could access the device (but not simultaneously) without the need to change cables. The ADC is a successive approximation type. The maximum sampling rate is 100 kHz and the settling time is 50 μ s. Gain is software-selectable in steps between 100mV to 10V (approximately doubling at each step). The output signals of the transducers used were conditioned to lie in the range $-5V$ to $+5V$. Signals were fed to the ADC via a specially made converter box enabling the use of standard BNC connectors.

The user has control of the data scan rate and how the data is written to data file. Signals from all transducers are scanned and displayed in panels appropriate to the type of signal being viewed. For example, parameters such as flow rates used to set up the test run are displayed in one panel whilst the performances of various parts of the rig are displayed in another. This reduces the information presented to the user in any one place. The user switches displays via a simple menu system.

Some signals are processed on-line, e.g. the superficial gas and liquid velocities and GVF at the inlet to the Venturi. These are not saved to file, but the transducer outputs from which they are derived, are.

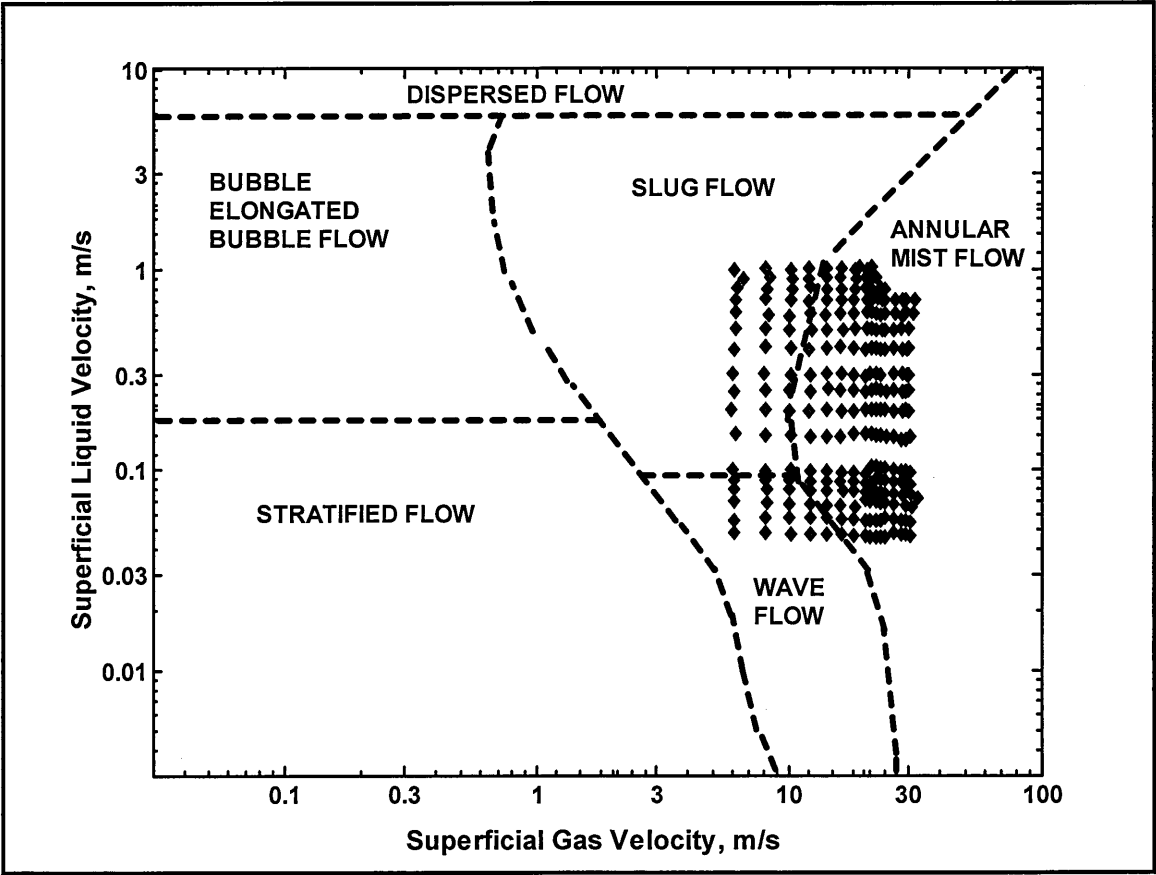
3.7 Test Matrix

The test matrix in this work covered a total of 272 data points as shown in Figure 3.8. The vast majority of data was collected in the annular/mist flow regime, but adequate numbers of points were also taken from wavy and slug flow regimes as well as in dry gas conditions. Although the present work was designed to focus mainly in the annular/mist flow regime, because of its dominance in wet gas flow conditions, however, in wet gas transportation pipelines it is common that other flow regimes can occur intermittently, particularly slug flow. In gas lift operations for example, it is very common for instantaneously slugs of liquids and gases to occur as the GVF can fluctuate between 95-100 %. For these reasons it is important that the application of pattern recognition techniques to wet gas flow metering be based on a comprehensive data set covering all the three main flow regimes that can occur in wet gas flow conditions (i.e. annular/mist, wavy and slug flow) as well as dry gas flow.

The test matrix is based on two main parameters; the superficial gas and liquid velocities. The selection of velocities is based on the well-known Mandhane et al (1974) flow regime map for horizontal two-phase gas-liquid flow systems. Note the cut in the top right hand corner of the test matrix as shown in Figure 3.8 refers to the annular/mist flow regime data that could not be obtained due to compressor limitations.

The experimental tests were carried out, typically by setting the liquid flow rate constant and increasing the gas flow rate (from left to right).

Figure 3.8: Test Matrix



This chapter reviewed the test rig and data acquisition system put in place to gather high quality data for the study of the applications of pattern recognition techniques to wet gas flow measurements. The next chapter will now detail the process of extracting and selecting relevant information in the form of features, using signal-processing techniques from the sampled data of the Venturi meter.

CHAPTER 4

FEATURE EXTRACTION AND ANALYSIS

This chapter discusses data pre-processing and feature extraction procedures developed in this work to convert the sampled data as outlined in the previous chapter into manageable and meaningful information that the pattern classifier (chapter 5) can infer the individual gas and liquid flow rates from.

4.1 Raw Data Analysis and Sensor Response to Flow Conditions

During experimental testing a number of techniques were used to ensure that the data collected was valid and that the sensors correctly responded to flow conditions. Sensor response as a function of time was graphed and monitored online so that any sensor malfunctioning could be detected immediately, as were the test parameters of GVF and superficial gas and liquid velocities. Following the online checking and after each set of tests, a more detailed analysis was carried out to validate and further ensure that the sensors were functioning correctly to the pre-defined test conditions. Figure 4.1 is a time domain representation of the Venturi throat differential pressure sensor (DP12), where the subset Figures 4.1a to 4.1d represent the dry gas, wavy, slug and annular mist flow conditions. It is clear that the sensor responds well to the prevailing flow conditions having a negligible pressure drop in the dry gas flow as this condition represents a stable and steady state flow, however as liquid is introduced, characterised by the wavy flow regime, the sensor responds to the hydrodynamic changes with a higher pressure drop than it did in the dry gas flow. A more distinct and transient flow behaviour is displayed in Figure 4.1c representing slug flow regime, where the superficial gas and liquid velocities are 10 and 0.5 m/s respectively. The high peaks indicate the high velocity slug of liquid propagating down the pipe conduit. As the gas velocity is increased even further a

slightly more stable condition is re-established by the formation of annular/mist flow regime and the sensor responds accordingly as evidently displayed in Figure 4.1d.

A similar response and behaviour can be seen in Figure 4.2a to 4.2d for the Venturi recovery length differential pressure sensor (DP13), where the sensor uniquely responds to each flow condition. The time domain representation of the absolute pressure sensor (AP01) is displayed by Figures 4.3a to 4.3d. The absolute pressure transducer was calibrated initially at the beginning of each run to atmospheric pressure ($1 \text{ atm} = 1.013 \text{ bar}$), however as liquid is introduced and flow conditions are varied, absolute pressure also changes accordingly responding to the prevailing flow conditions.

Figure 4.4 shows a scatter plot of the responses of pressure sensors as a function of liquid loading and superficial gas velocity. As would be expected the magnitude response of each pressure sensor increases as the liquid loading and gas velocity were increased.

An observed phenomena from Figure 4.4b is that as the liquid loading is increased beyond 0.3 m/s , the recovery length pressure drop (DP13) exceeds that of the Venturi throat pressure drop (DP12) and hence results without the expected pressure recovery from the Venturi as the flow channel is expanded to the pipe size. As shown in the test matrix of Figure 3.8 this threshold of liquid velocity (i.e. 3 m/s) conforms to the slug and the high liquid content of annular/mist flow regime. It was observed during the experimental testing that the Venturi throat acts as a flow conditioner/mixer under these flow regimes such that the high liquid content mixture flow with the thick liquid layer/film that entered the throat leaves it as a diverging misty jet and continues to be accelerated even as the flow channel is expanded to the pipe size. This could mean that because the kinetic energy (mixture velocity) is now increased in the expansion section as a result of the change of flow regime caused by the throat (i.e. from slug and high liquid content of annular flow to a fully misty jet) the pressure energy is therefore decreased in the divergent section as compared to the throat and hence DP13 becomes greater than DP12 under these conditions. The results here support the findings published by Amini et al (1991), who conducted experimental work on two-phase flow (air-water) using a conical diffuser and found that pressure recovery reduces as the liquid loading is

increased. However unlike the current study their experimental matrix didn't reach the point of no pressure recovery.

The motivation behind the application of pattern recognition techniques to wet gas flow measurements (as well as the neighbouring flow regimes) in the current research work, stems from this distinct sensor behaviour in different flow conditions. It is the objective of this research work to investigate the feasibility of developing a Venturi based pattern recognition system that can recognise the inherent hydrodynamic and sensor behaviour in different flow regimes and thereby infer the individual gas and liquid flow rates exist therein from it.

Figure 4.1: Venturi Throat DP Response to Flow Conditions

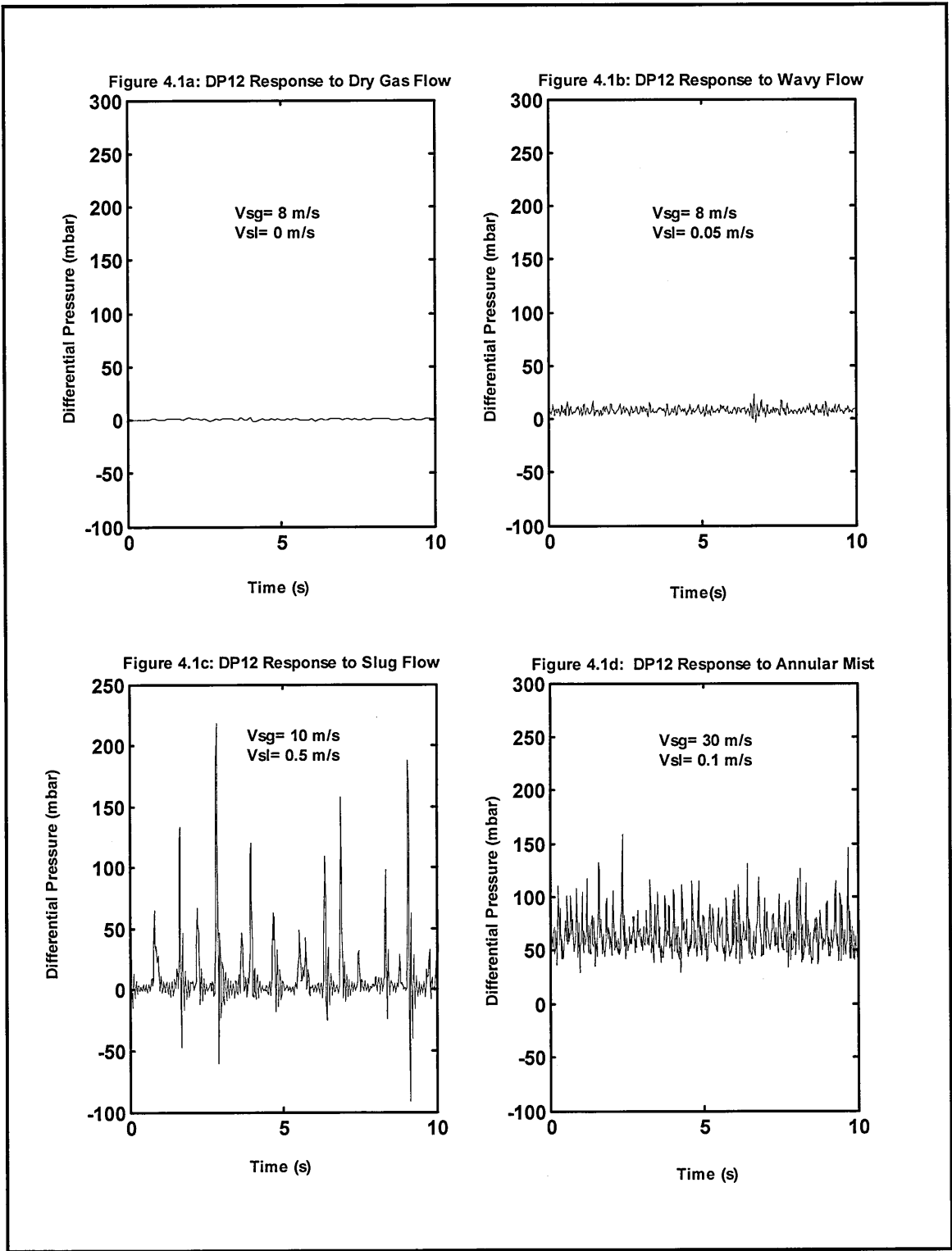


Figure 4.2: Venturi Recovery Length DP Response to Flow Conditions

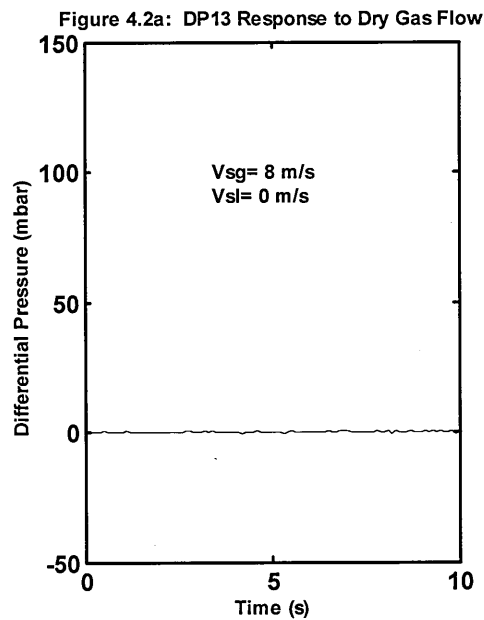
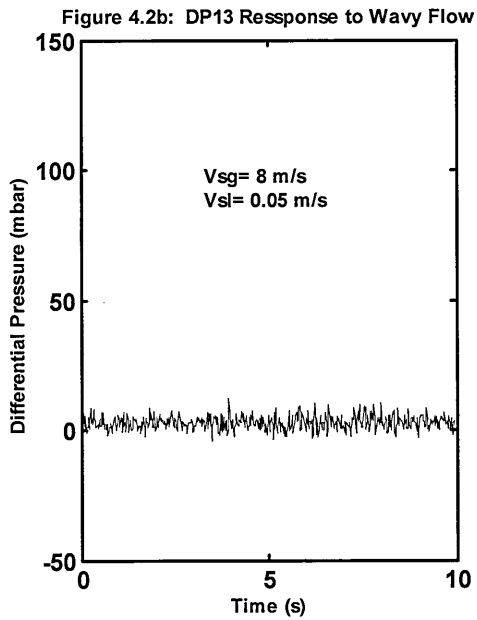
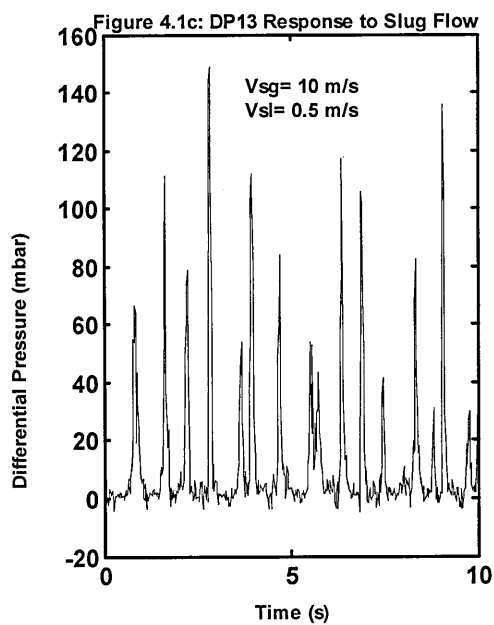
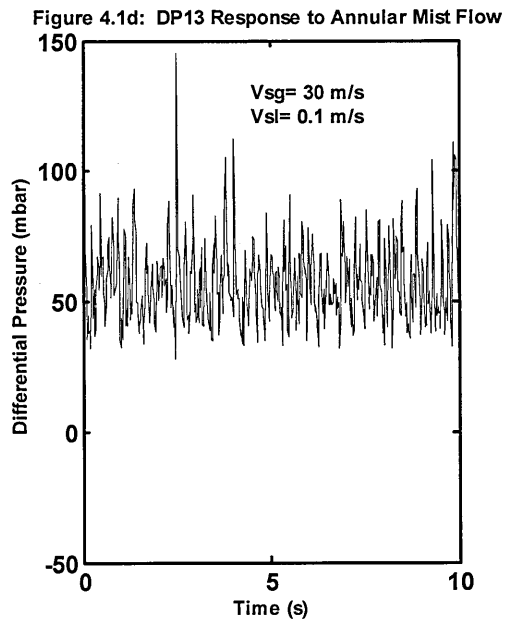


Figure 4.3: Venturi Absolute Pressure Response to Flow Conditions

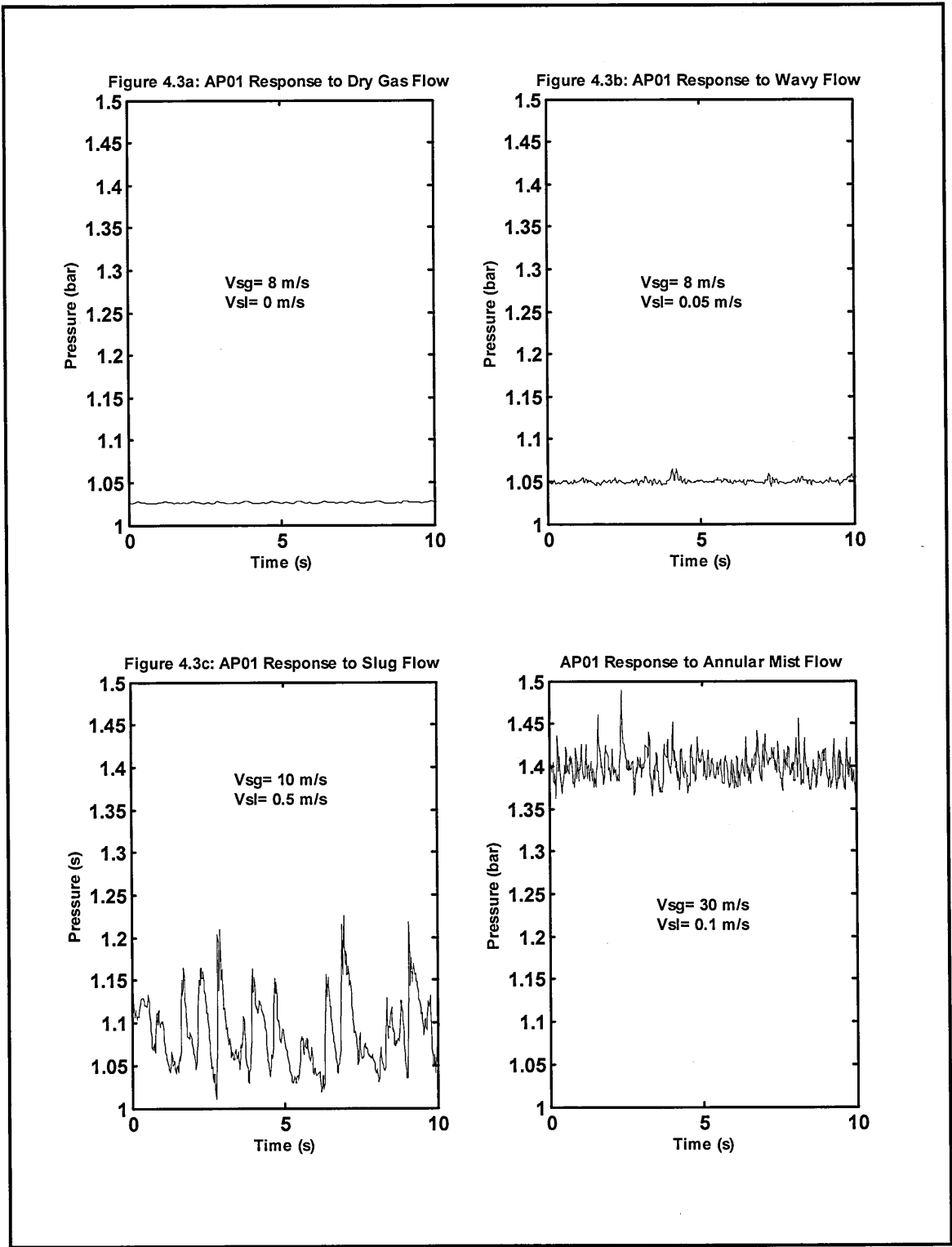
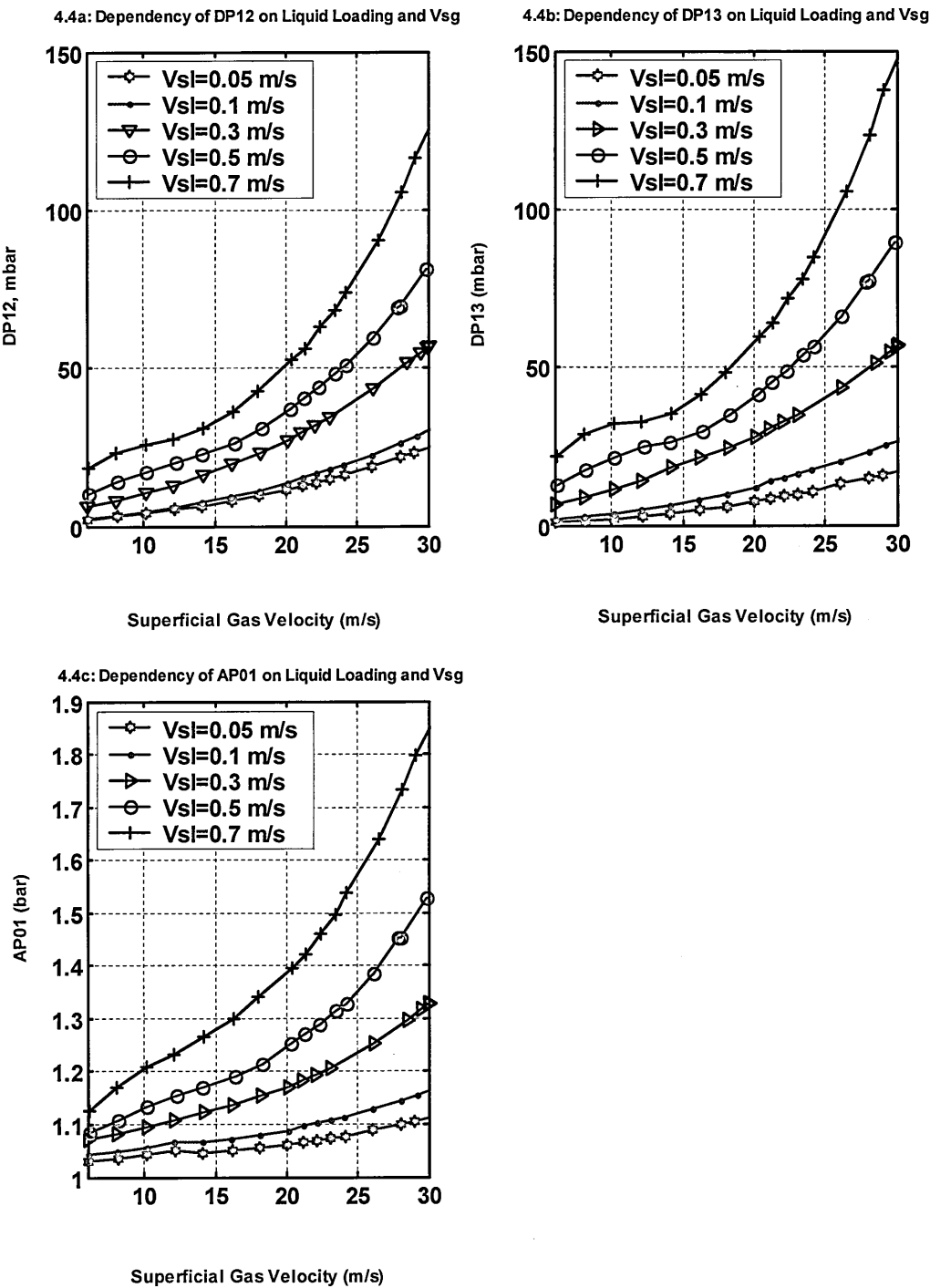


Figure 4.4: Pressure Sensor Responses to Liquid Loading and Gas Velocity



4.2 Feature Extraction and Dimensionality Reduction Test

The most common difficulty in pattern recognition is usually the vast amount of information, which has to be dealt with. There are two main reasons why the raw pressure data could not be used: in the first instance a neural network with prohibitively too large number of free parameters (weights and biases) would be required to populate the 3251-dimensional (50Hz x 60 seconds) input space. Secondly as mentioned in chapter 2 (section 2.4.5), previous studies in the application of pattern recognition techniques confirmed that the discriminatory information in multiphase flow measurements lies with feature extraction. Consequently a feature extraction approach was adopted in order to reduce the dimensionality of the raw data. With the help of digital signal processing techniques, there are an infinite number of features that can be extracted from different information domains. In the current study a number of features were extracted from time and frequency domains. A preliminary analysis had shown that some of these features (e.g. autocorrelation coefficients) did not demonstrate any significant discriminatory ability and resulted with very poor network classification accuracy and were therefore eliminated from further processing. The features extracted from each pressure sensor that were found discriminative to the varying flow conditions are summarised in Table 4.1, in terms of amplitude, linear prediction coefficients (LPC) and line spectral frequencies (LSF). The amplitude features are calculated for each test point as described in chapter 2.

The LP coefficients are obtained from standard linear prediction analysis, based on blocks of input samples as described in chapter 2. At different flow conditions of gas and liquid flow rates, a variation in energy and spectral characteristics can occur in a short time interval. Therefore there will be a change in the LP coefficients in consecutive blocks of different pressure waveforms. Since LP coefficients provide a simple and effective method of representing different signals in terms of small number of parameters, they can be used not only a way of data compression but also as a supply for different statistical features for different flow conditions. The feature-set response and variation with respect to specific waveform of differential pressure and absolute pressure

will be examined in this chapter by using distribution/contour-mapping techniques. The line spectral frequencies are a representation of the LP parameters in the frequency domain and they have a shorter dynamic range of values and hence have a better quantisation ability than LP parameters as mentioned in chapter 2. The LSFs will too be evaluated for their discriminatory ability for different flow conditions using contouring techniques.

Table 4.1: Summary of Features Extracted from each Information Domain

Nº	Feature	Symbol	Amplitude	LPC	LSF
1	Average Value	AV	✓		
2	Standard Deviation	SD	✓		
3	Coefficient of Variation	CV	✓		
4	Coefficient of Skewness	CS	✓		
5	Coefficient of Kurtosis	CK	✓		
6	Signal Total Energy	E _T	✓		
7	Linear Prediction Coefficient 1	A1		✓	
8	Linear Prediction Coefficient 2	A2		✓	
9	Linear Prediction Coefficient 3	A3		✓	
10	Linear Prediction Coefficient 4	A4		✓	
11	Linear Prediction Coefficient 5	A5		✓	
12	Linear Prediction Error	E _p		✓	
13	Line Spectrum Frequency 1	LSF1			✓
14	Line Spectrum Frequency 2	LSF2			✓
15	Line Spectrum Frequency 3	LSF3			✓
16	Line Spectrum Frequency 4	LSF4			✓
17	Line Spectrum Frequency 5	LSF5			✓

A number of methods were initially tested for pre-processing the input feature vectors.

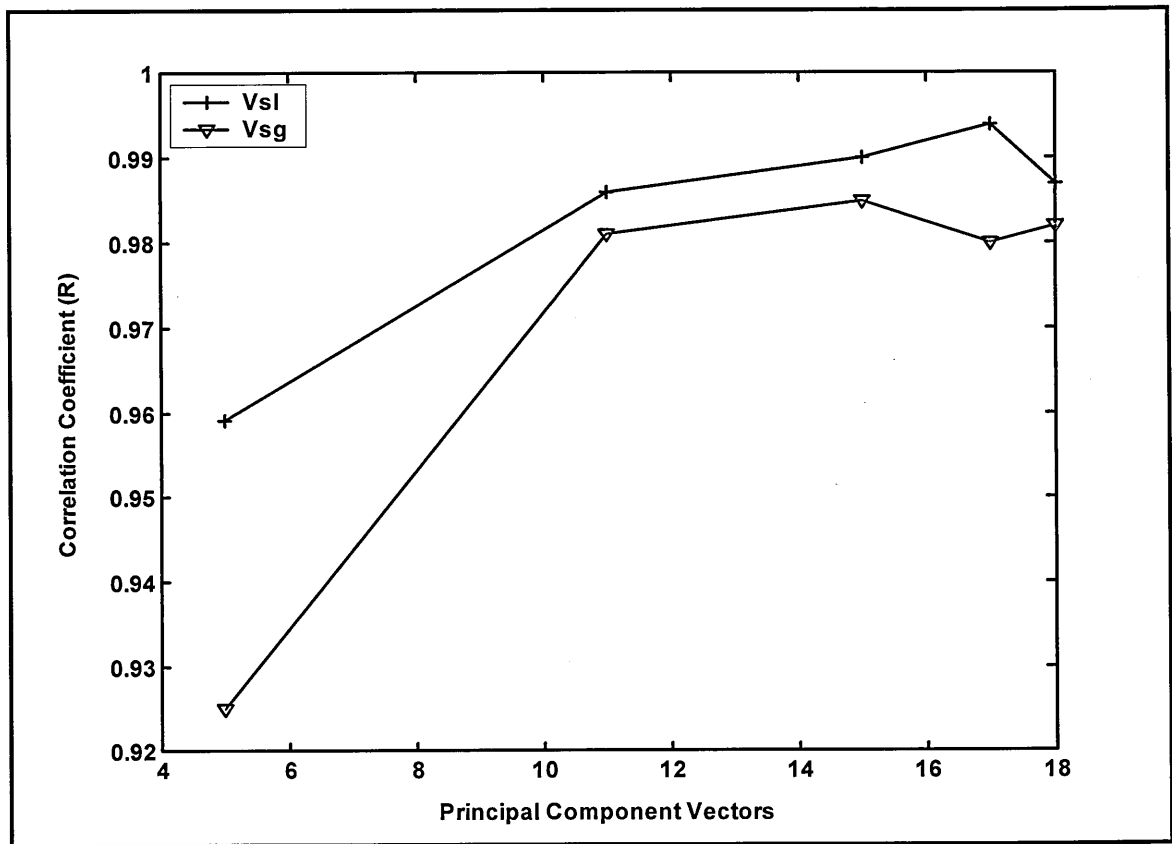
1. One method was to normalise the input features to the pattern classifier so that they fall in the range of $[-1, 1]$.
2. Another normalisation technique was to equalise the magnitude and dynamic range of each feature by applying zero mean and unit-variance normalisation to the feature vectors. Here the data values are centered (i.e. subtract the mean values from the data values in order to obtain centered anomalies) and then divide by their standard deviations to obtain a normalised data having zero mean and unit variance.
3. A third pre-processing technique was to transform the input feature vectors into a new feature space, which are uncorrelated and orthogonal to each other by the use of principal component analysis (PCA). A MATLAB routine called PREPCA was used for this purpose. Those components, which contribute only a small amount to the total variance in the data set, can be eliminated.

The classification accuracies obtained from the above three pre-processing techniques were compared using feature vectors extracted from each information domain for each pressure sensor as well as combination of different feature vectors. A Bayesian MLP neural network was used for the classification of gas and liquid flow rates. The results indicated that in terms of normalisation methods, the zero mean and unity standard deviation technique results with much better classification accuracy than the simple technique of scaling the data in the range of $[-1, 1]$. This may be due to the fact that the latter technique ensures that all features are given equal emphases by equalising the magnitude and dynamic range of each feature by applying zero mean and unit-variance normalisation to the feature vectors.

Although the limited dimension of the extracted features in the current study may not necessitate a further feature pruning and dimensionality reduction process, nevertheless

since it is a common practice in many applications to use a principal components analysis (PCA) method to guide the choice of a subset of features from a larger candidate set, it was considered necessary to verify its applicability in the current research work. Hence the application of PCA was carried out and its classification accuracies compared against the above-mentioned normalisation techniques. It turned out that when PCA was used to orthogonalise the input features so that they are uncorrelated without feature reduction, its accuracies were compatible to those obtained when the input features were normalised with zero mean and unity standard deviation. The second trial of PCA was to employ it in dimensionality reduction mode, such that those transformed feature vectors that contribute less than a predefined percent (typically 0.1%) to the overall variability are eliminated. As shown in Figure 4.5, the dimensionality reduction by PCA reduces the classification accuracies of the network as those features with the least variance are eliminated. It was observed that this trend in PCA performance was consistent regardless of the type of the pressure sensor(s) and feature vectors used.

Figure 4.5: Evaluation of Principal Component Analysis (PCA)



The preliminary feature pre-processing exercise showed that the decorrelation and high measures of statistical significance provided by the first few principal component axes are no guarantees of having the best subset of features. PCA finds feature combinations that model the variance of a data set, but these may not be the same features that separate the classes, i.e. the PCA components that model the largest contributions to the data set variance may work poorly for pattern recognition and may not be suitable for discriminating between underlying classes as applied to the current study. It was also seen that the popular practice of ignoring the lower-order PCA components in order to achieve dimensionality-reduction had in fact resulted in losing some of the discriminatory information present in the data.

It can be stated that in applications similar to the current study, wherein the dimensions of the raw data is already significantly reduced by extracting features which are considered useful, the use of PCA as a further dimensional reduction procedure is not recommended because of its computational complexity without necessarily achieving improved classification accuracies. Due to the encountered limitations of PCA in the current study, it was omitted from the present pattern recognition system. In certain applications, however, when the input data has high dimensions and there are no obvious features which can be extracted from it, the input dimensionality must nevertheless be reduced in order to limit the number of free parameters in the pattern classifier, in these cases PCA may be a suitable technique to apply for dimensionality reduction.

In this study, as a feature pre-processing technique a zero mean and unit-variance normalisation procedure was applied to the input features. This serves to equalise the magnitudes and dynamic ranges for each feature, but leaves the relative overlap between the different features unchanged.

It is important to visualise each feature's variation over the flow domain of interest. A useful technique, which facilitates feature trend visualisation, is contour plots. This technique allows the visualisation of three-dimensional data on two-dimensional plots. A contour plot of vector Z over (X, Y) plot treats the values in Z as heights above a plane.

In the current study, the contours are the level curves of the feature vectors over the intersection grid values of superficial gas and liquid velocities. This provides the ability to visualise how each feature is responding to the changes in flow conditions. It is necessary to select a suitable number of contour levels, as too many contours would render the technique ineffective for providing the required visualisation, while too few contours will not capture the overall feature spectrum. In this study 15 linearly spaced contour levels including minimum and maximum of each normalised feature was considered optimum for feature trend visualisation purposes. Actual test data points are superimposed on the same plot for better visualisation of the contour trends and flow regime boundaries that delineate each flow regime as visually observed are also plotted on the graph to see feature trends over different flow conditions. The contour plots represent the normalised features, as this will be the input to the pattern recognition classifier, and not the original features sets.

4.2.1 Venturi Throat Differential Pressure (DP12)

Figure 4.5a to 4.5f display the normalised feature distribution maps of the amplitude domain of throat differential pressure, DP12 (see Figure 3.3 for schematic location of throat DP). Note the cut in the top right hand corner of all the contour figures refers to the annular/mist flow regime data that could not be obtained due to compressor limitations. Also note that the flow regime boundaries plotted over the contour maps are based on the observations made during the experimental testing.

The average value (AV) feature displays a definite and unbiased response to both gas and liquid velocities across the whole flow regimes examined. The standard deviation (SD) feature displays a flat response in the wavy and annular mist flow regimes, but only up to a liquid velocity of 0.4 m/s. However, at a superficial gas velocity of 15 m/s, and as the liquid velocity is increased beyond 0.4 m/s, which corresponds to the slug flow regime, the SD feature contours curl upwards and continue with this trend throughout the slug flow regime. At the start of the annular/mist flow regime the feature contours begin to decline and continues declining across the annular/mist flow regime, until it reaches a

superficial gas velocity of around 24 m/s, at which point it starts to flatten out again. This is extremely useful information, especially as these changes occur at the boundary between slug and annular/mist flow regimes and indicate that the feature is flow regime dependent. From a pattern recognition stand point, the distinct feature behaviour in the slug flow regime means that if the system is trained on wet gas flow data only (annular/mist) flow regime and if the system experiences slugging conditions, its measurement accuracy may be effected because of the drastic changes in feature behaviour. However less marked and better classification accuracies might be expected in the wavy flow regime, as the feature trends are quite similar in the wavy and annular/mist flow regimes. Section 5.4.6 of chapter 5 investigates the effect of flow regime change on pattern recognition measurement results.

The coefficient of variation (CV) feature appears to be most affected by the liquid loading than gas velocity. The feature responds most markedly to the hydrodynamic changes of the slug flow regime, however the feature trends disappear in the wavy and annular/mist flow regimes. Both the coefficient of skewness (CS) and coefficient of kurtosis (CK) show strong dependency on liquid loading, particularly in the slug flow regime as they attain higher feature values in this region than other flow regimes. The trend response of the total signal energy (E_T) starts at a liquid velocity above 0.6 m/s. Below this point, the feature does not appear to have any trend, which from a pattern recognition viewpoint will mean that this feature will not provide any discriminating ability in the wavy, slug and annular/mist flow regimes for the current test conditions below a liquid velocity of 0.6 m/s.

The feature distribution maps of the linear prediction coefficients of the throat DP are shown in Figures 4.6a to 4.6f. The first four linear prediction coefficients (A1-A4) appear to display strong response in the slug and in the annular/mist flow regimes, particularly at a superficial liquid velocity greater than 0.5 m/s. The fifth linear prediction coefficient (A5) shows to be sensitive to both the gas and liquid flow rates

across the whole flow domain of interest. The sensitiveness of the linear prediction residual error (E_p) appears to begin at a superficial liquid velocity of 0.5 m/s.

Figures 4.7a to 4.7f display the feature distribution maps of the line spectral frequencies of the throat DP. The first line spectral frequency (LSF1) appears to be influenced by the liquid loading with most noticeable liquid dependency seen in the slug flow regime. The feature has no significant visible trends associated with it in annular/mist flow regime. The line spectral frequency 1(LSF1) feature shows to be strongly sensitive to hydrodynamic flow changes in all the three flow regimes. The line spectral frequency 3 (LSF 3) produces a uniform and flat response in the wavy flow regime and in the annular/mist flow, mainly below liquid velocity of 0.3 m/s. Above this liquid velocity the feature contours appear to be effected by the variation of both gas and liquid velocities. Both the LSF4 and LSF5 demonstrate similar response behaviour to changes in flow conditions in all the three flow regimes. These features do not appear to have a traceable response in the area having liquid velocity between 0.3 and 0.6 m/s, which corresponds to slug and annular/mist flow regimes.

Figure 4.5: Amplitude Features Distribution Maps of Throat DP

Figure 4.5a: AV Feature of Throat DP

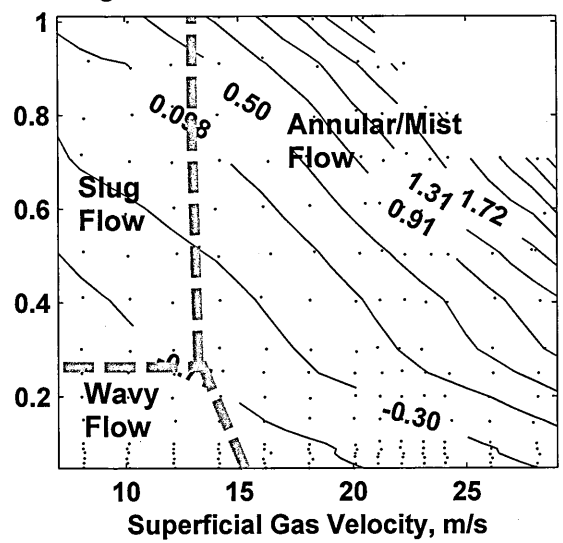


Figure 4.5b: SD Feature of Throat DP

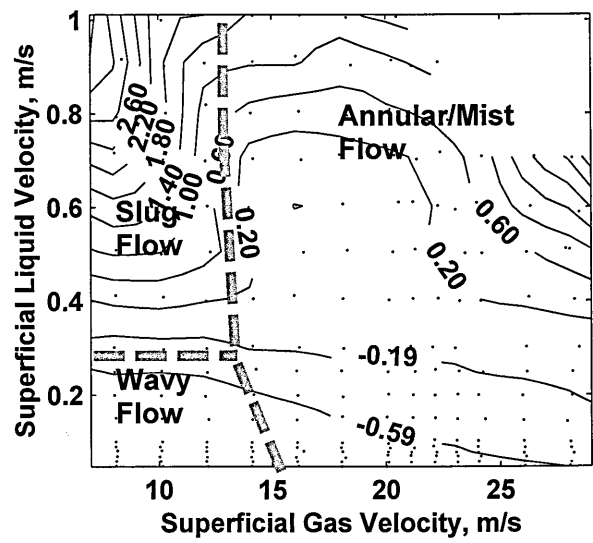


Figure 4.5c: CV Feature of Throat DP

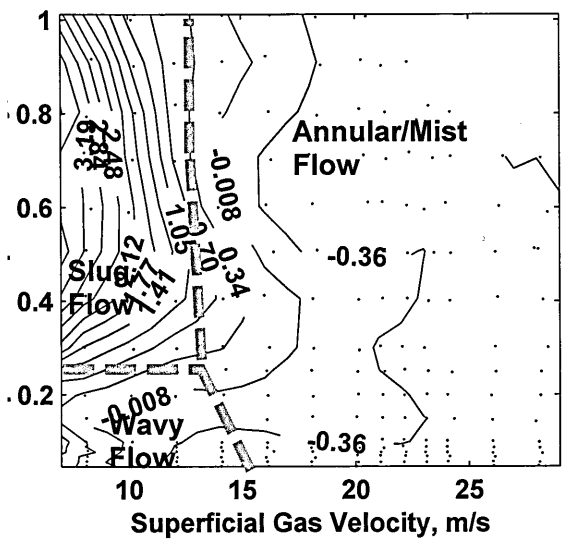


Figure 4.5d: CS Feature of Throat DP

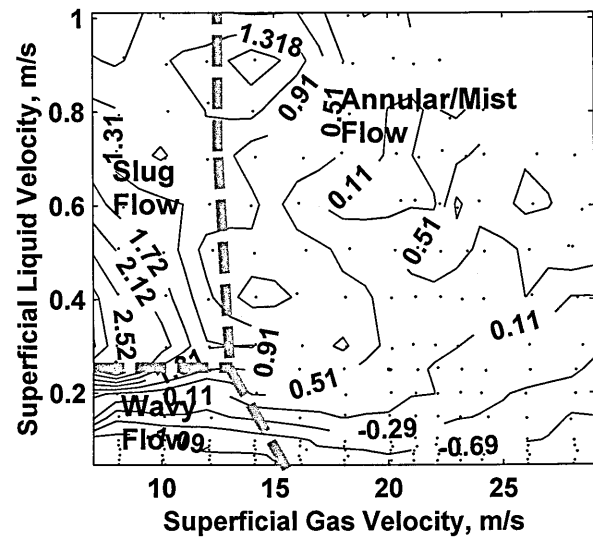


Figure 4.5e: CK Feature of Throat DP

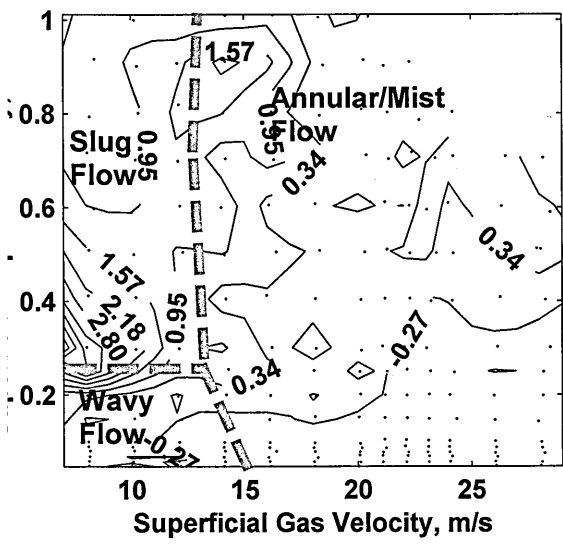


Figure 4.5f: ET Feature of Throat DP

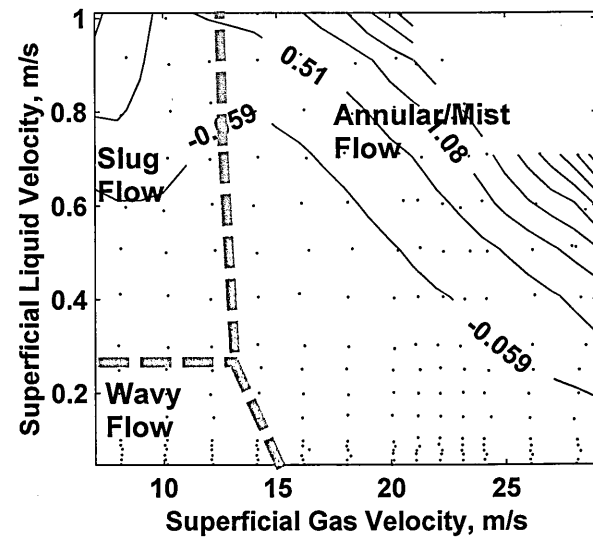


Figure 4.6: LPC Features Distribution Maps of Throat DP

Figure 4.6a: A1 Feature of Throat DP

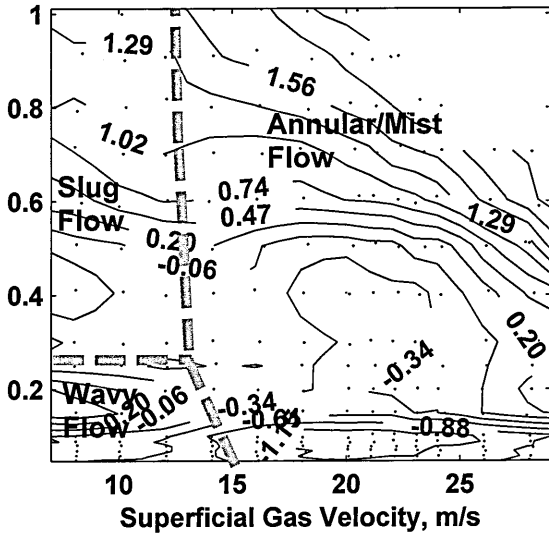


Figure 4.6b: A2 Feature of Throat DP

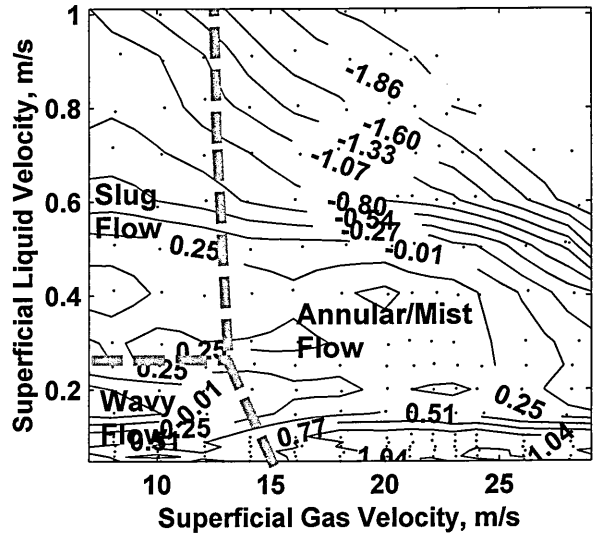
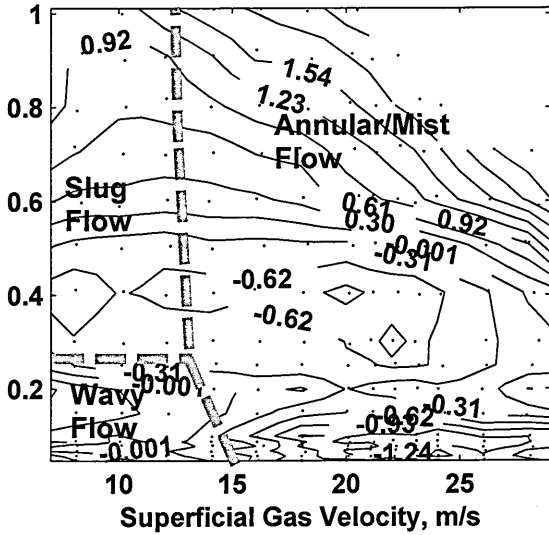


Figure 4.6c: A3 Feature of Throat DP



4.6d: A4 Feature of Throat DP

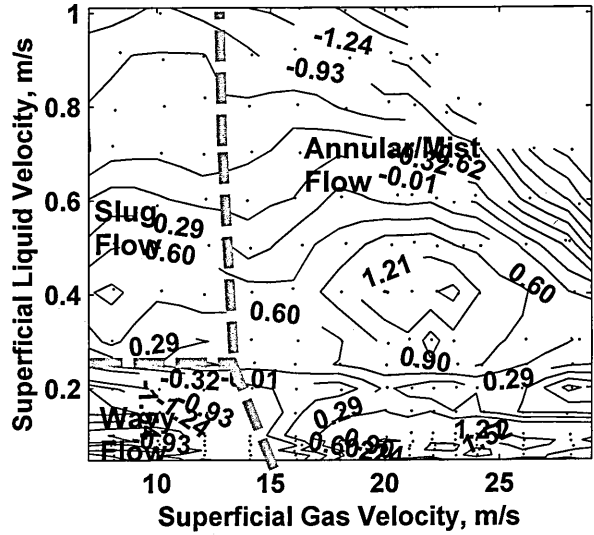


Figure 4.6e: A5 Feature of Throat DP

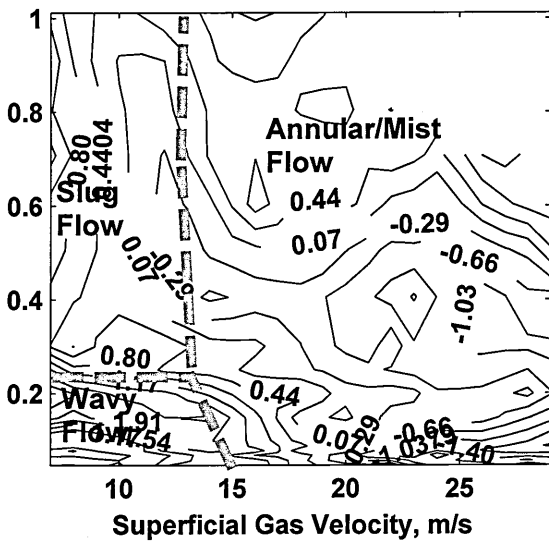


Figure 4.5f: Ep Feature of Throat DP

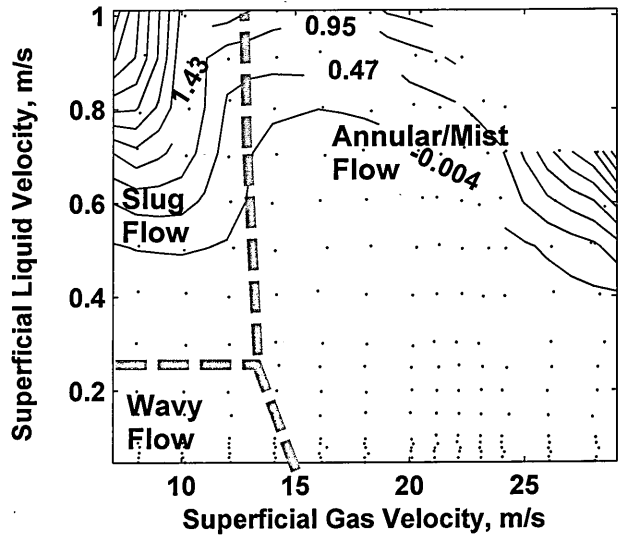


Figure 4.7: LSF Features Distribution Maps of Throat DP

Figure 4.7a: LSF1 Feature of Throat DP

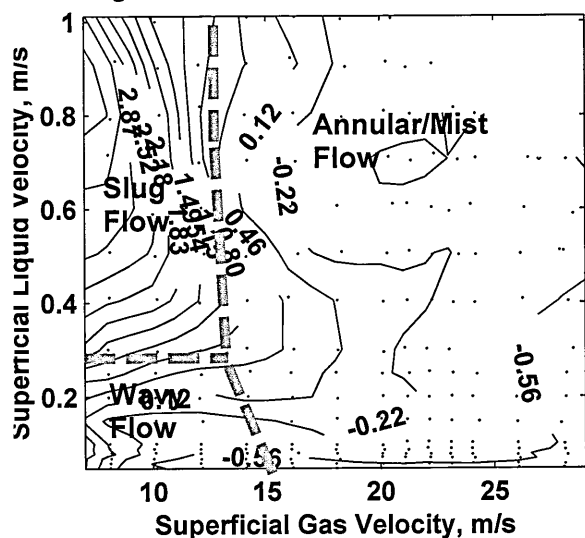


Figure 4.7b: LSF2 Feature of Throat DP

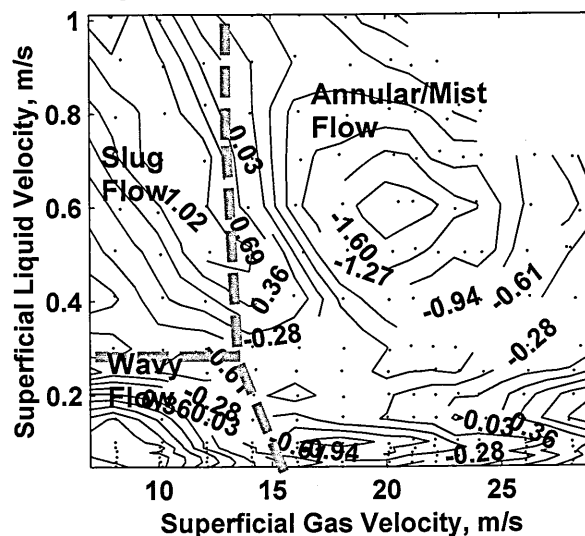


Figure 4.7c: LSF3 Feature of Throat DP

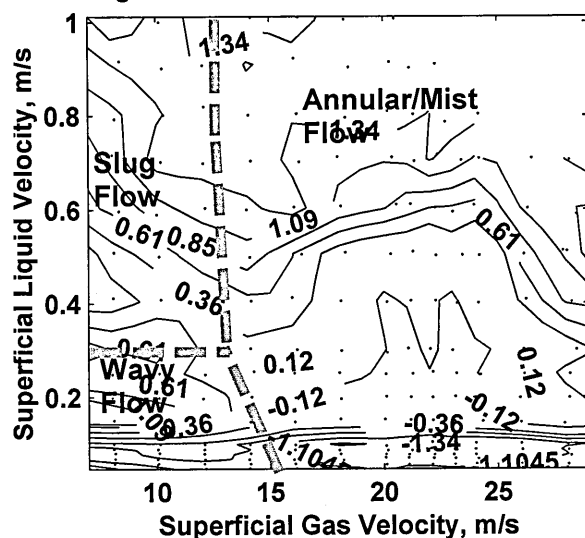


Figure 4.7d: LSF4 Feature of Throat DP

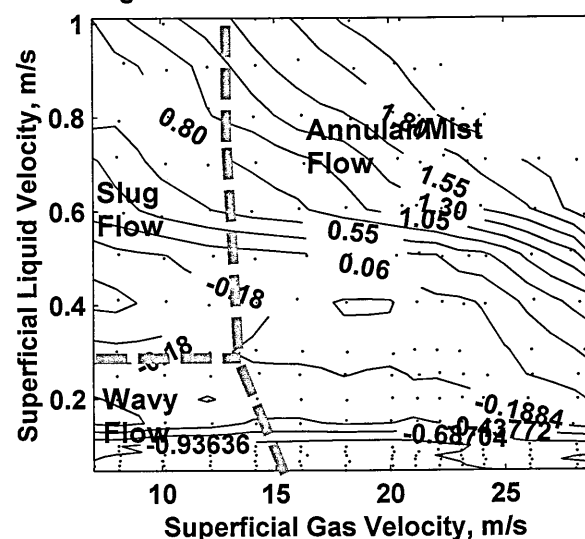
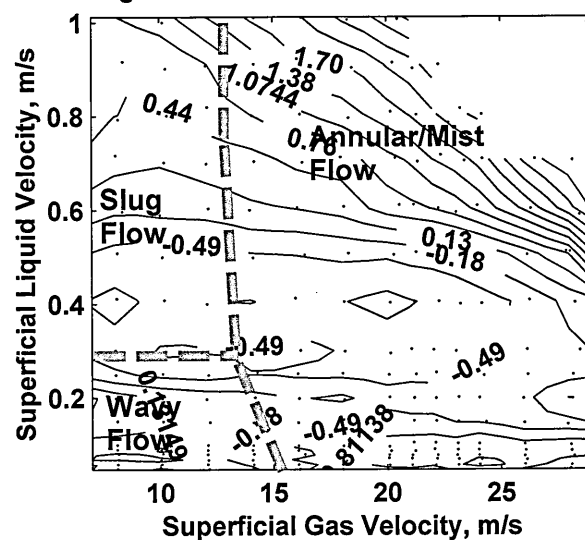


Figure 4.7e: LSF5 Feature of Throat DP



4.2.2 Venturi Recovery Length Differential Pressure (DP13)

The amplitude feature distribution maps of the recovery length DP (referred to as recovery DP for short) are shown in Figures 4.8a to 4.8f. The AV feature displays uniform sensitivity behaviour to both gas liquid velocities in all the three flow regimes studies. The SD feature appears flat in all the three flow regimes, however, above a superficial liquid velocity of 0.4 m/s and beyond superficial gas velocity of 15 m/s, the contours start to curl upwards, displaying a particular sensitivity in slug and annular mist flow regimes. The CV appears to be most effected by the liquid loading, especially in the slug flow regime, where the feature has all its values concentrated. The CS and CK values exhibit similar distribution and display a complex trend over the flow domain of interest with sensitivity to both gas and liquid velocities. The total signal energy feature (E_T) becomes sensitive to flow conditions only as the superficial liquid velocity is increased beyond 0.6 m/s.

The feature distribution maps of the linear prediction coefficients of the recovery DP are shown in Figures 4.9a to 4.9f. The first linear prediction coefficient (A1) demonstrates horizontally smooth contours in the wavy and in the annular/mist flow regimes up to a liquid superficial velocity of 0.3 m/s. As the liquid loading is increased the feature shows more sensitivity to the liquid by curling upwards. The second linear prediction coefficient (A2) displays similar trend behaviour as A1 in the wavy and in annular/mist flow regimes below a superficial liquid velocity of 0.3 m/s. However as the liquid loading is increased above this value, the feature displays a more complex contour behaviour, which is indicative of its strong dependency on liquid loading. The features A3 to A5 have a rather noisy and complex behaviour across the whole flow domain of interest. The linear prediction residual error (E_p) starts to become sensitive to flow condition above a superficial liquid velocity of 0.4 m/s. This distribution map is similar to that of the E_p of the throat DP.

The contour plots of the line spectral frequencies of the recovery DP are shown in Figures 4.10a to 4.10f. The LSF1 feature appears to be significantly affected by the liquid loading than the gas superficial velocity. The feature displays particular sensitivity to the liquid loading in the slug flow regime, where it can be seen to curve upwards as the superficial liquid velocity is increased. The contour maps of LSF2 to LSF4 appear to be similar, showing flat distribution in the wavy and in the annular/mist flow regimes below 0.3 m/s of superficial liquid velocity and having a more irregular contouring behaviour above this threshold. The distribution contour plots of the fifth line spectral frequency (LSF5) displays a more irregular and a complex trend across flow domain.

Figure 4.8: Amplitude Features Distribution Maps of Recovery Length DP

Figure 4.8a: AV Feature of Recovery DP

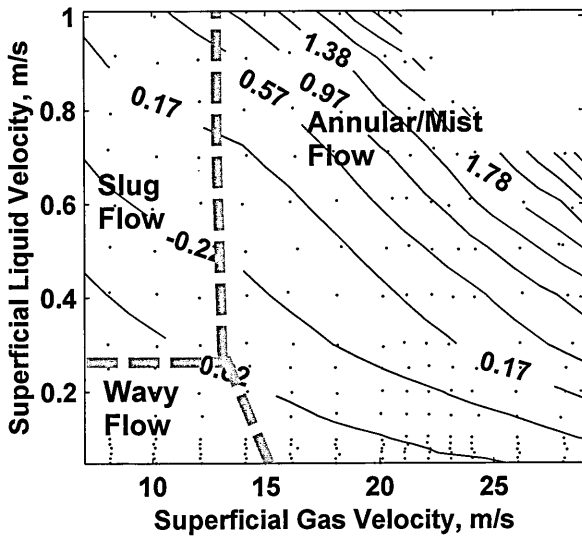


Figure 4.8b: SD Feature of Recovery DP

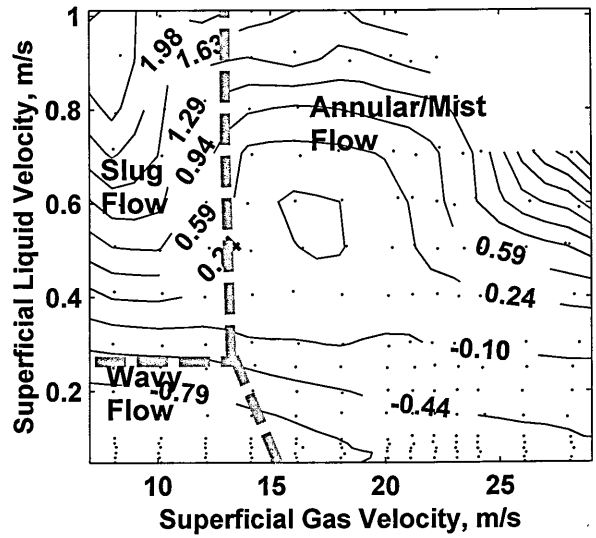


Figure 4.8c: CV Feature of Recovery DP

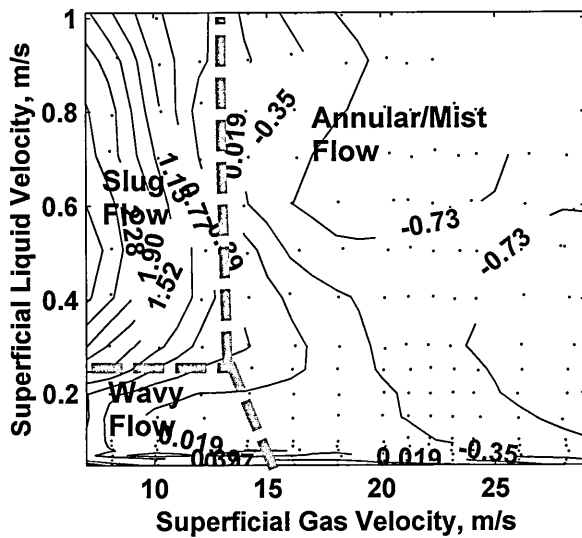


Figure 4.8d: CS Feature of Recovery DP

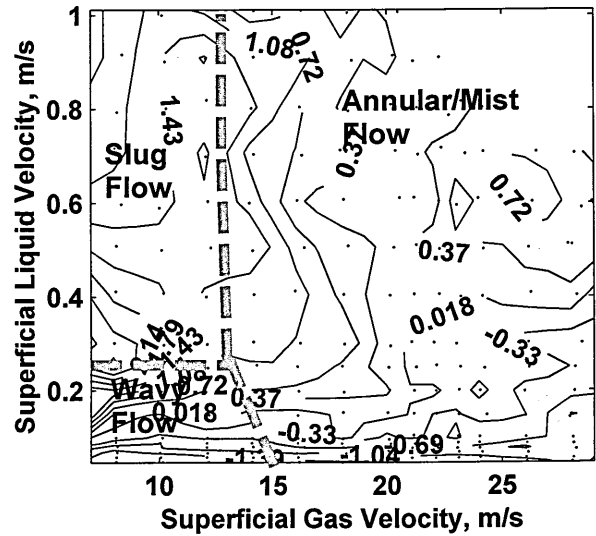


Figure 4.8e: CK Feature of Recovery DP

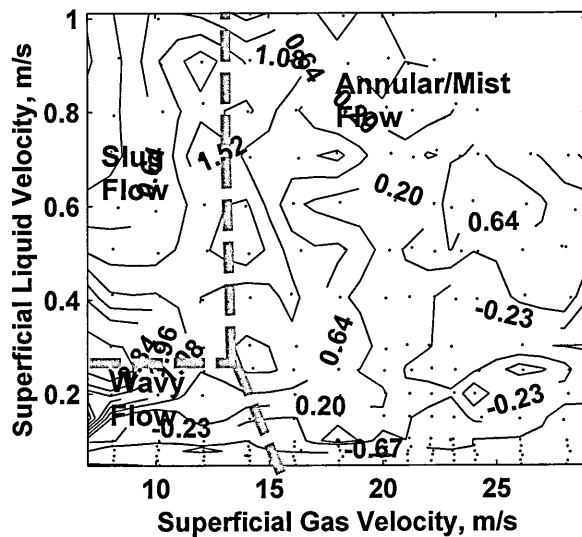


Figure 4.8f: ET Feature of Recovery DP

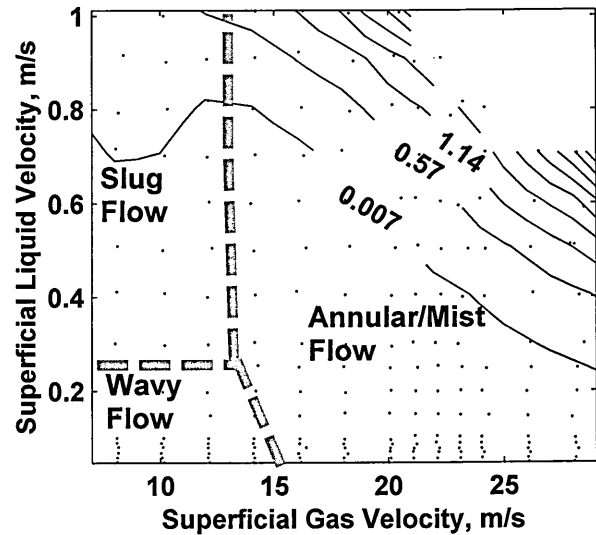


Figure 4.9: LPC Features Distribution Maps of Recovery Length DP

Figure 4.9a: A1 Feature of Recovery DP

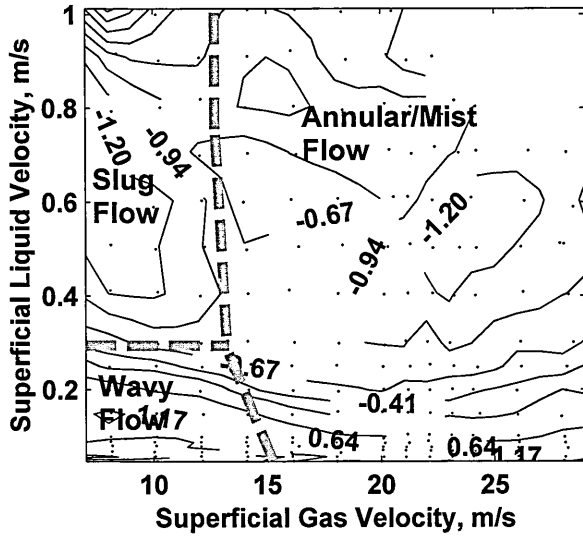


Figure 4.9b: A2 Feature of Recovery DP

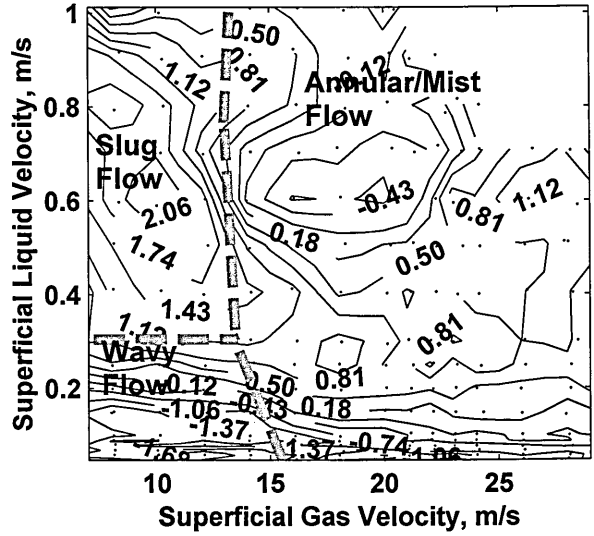


Figure 4.9c: A3 Feature of Recovery DP

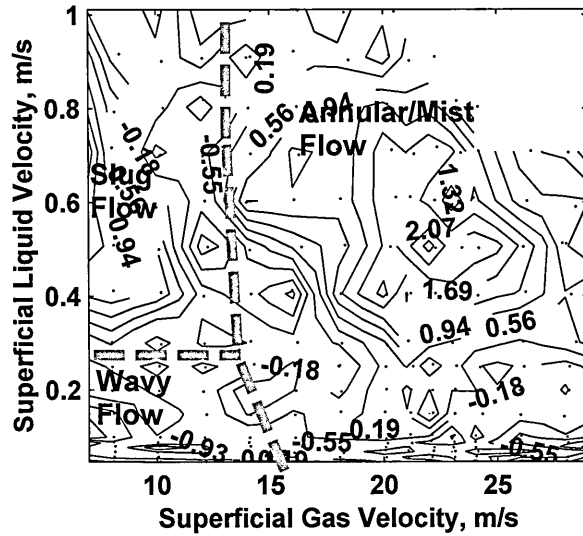


Figure 4.9d: A4 Feature of Recovery DP

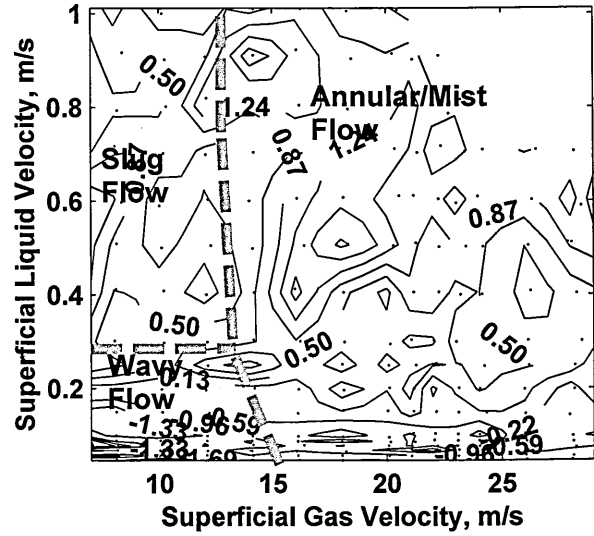


Figure 4.9e: A5 Feature of Recovery DP

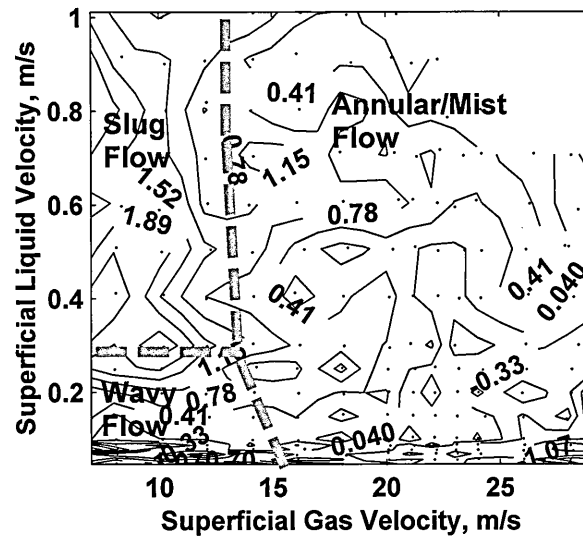


Figure 4.9f: Ep Feature of Recovery DP

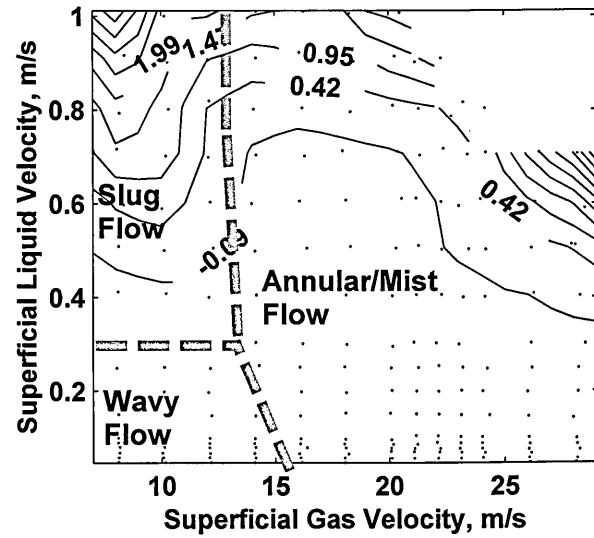


Figure 4.10: LSF Features Distribution Maps of Recovery Length DP

Figure 4.10a: LSF1 Feature of Recovery DP

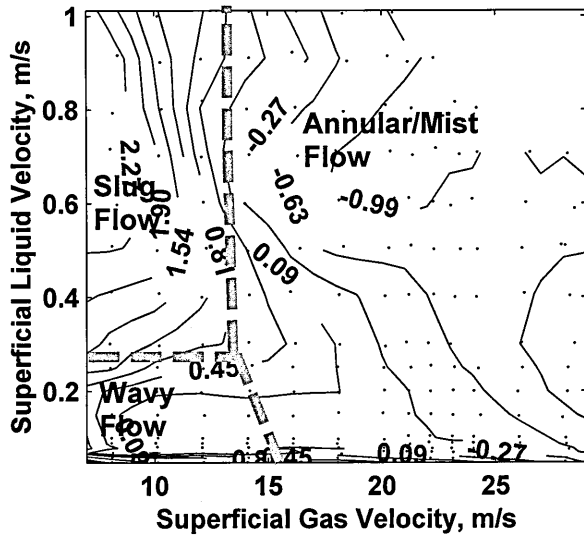


Figure 4.10b: LSF2 Feature of Recovery DP

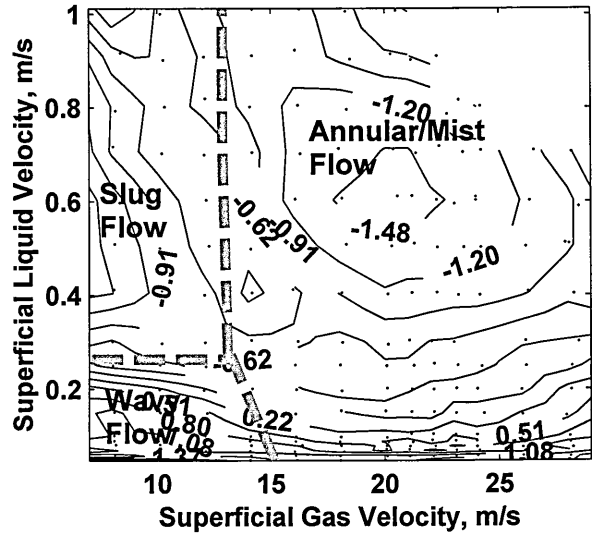


Figure 4.10c: LSF3 Feature of Recovery DP

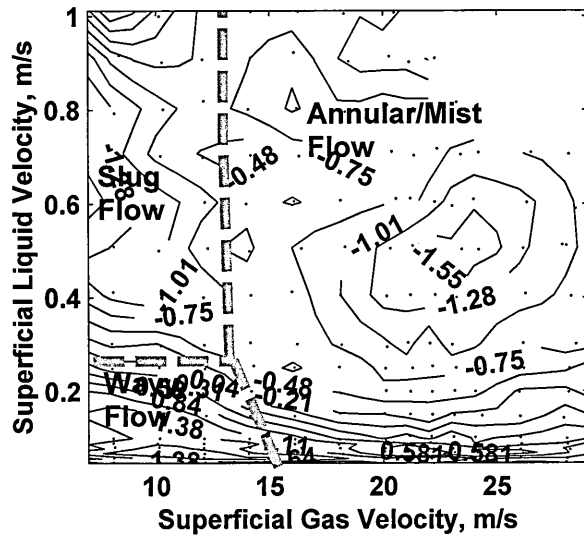


Figure 4.10d: LSF4 Feature of Recovery DP

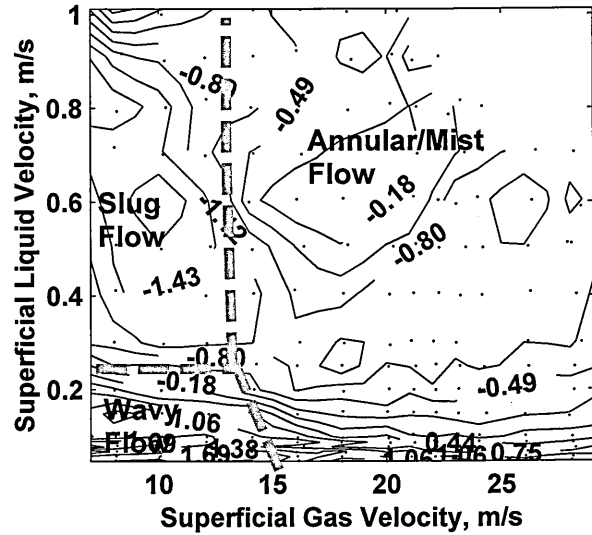
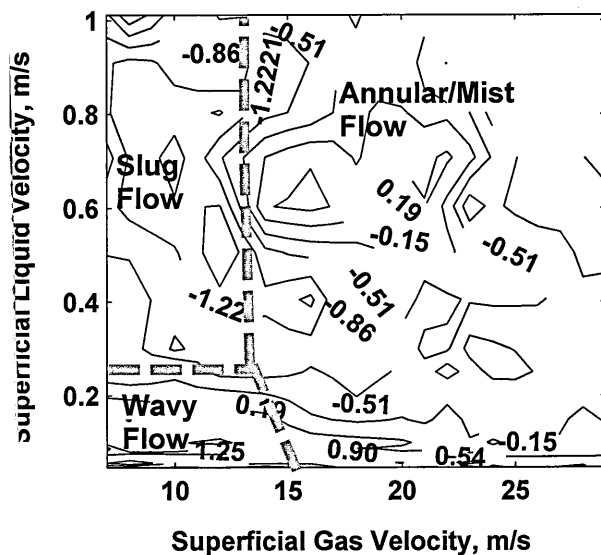


Figure 4.10e: LSF5 Feature of Recovery DP



4.2.3 Venturi Absolute Pressure Signal (AP01)

Unlike the differential pressure sensors, the AP01 sensor measures the absolute pressure of upstream fluid of the Venturi section. It should therefore be expected that some of the features extracted from this sensor would have a different distribution map to the aforementioned differential pressure sensors. The amplitude feature distribution maps of the absolute pressure signal are shown in Figures 4.11a to 4.11f. As would be expected the AV feature contours increase linearly with the increase in liquid loading and gas velocity and has a uniform feature distribution to both gas and liquid superficial velocities across the whole flow domain, a trend, which is similar to those, exhibited by both of the above differential pressure sensors. The standard deviation (SD) feature has a flat trend distribution in the wavy and in the annular/mist flow regimes, however, as the liquid loading is increased above 0.3 m/s and in the slug flow regime, the feature contours start to curl upwards. As the annular flow regime border is crossed, the contours begin to decline and become flat as the gas velocity is increased beyond 25 m/s. The SD feature distribution is quite similar to those of DP12 and DP13 in the wavy and in the slug flow regimes, but does not show a continued peaking into the annular/mist flow regime as the differential pressure sensors.

The CV feature of the absolute pressure sensor is responding most markedly to the liquid loading, particularly in the slug flow regime, where similar to the SD feature, the contours curl upwards. Like the SD feature, the CV feature also has most of its high feature values in the slug region. The CS and CK features display a rather scattered distribution over flow domain, and is not possible to draw any definitive conclusion from their trend behaviour. The feature distribution maps of the total signal energy (E_T) are quite similar to those of AV feature, and unlike the differential pressure sensors (DP12 and DP13), have a uniform sensitivity distribution across the whole flow domain of interest.

The feature distribution maps of the linear prediction coefficient are displayed in Figures 4.12a to 4.12f. The A1 feature only displays visible distribution above a liquid velocity of 0.6 m/s. The A2 feature appears to be strongly sensitive in the slug flow regime, but the feature stretches out significantly into the annular/mist flow regime above superficial liquid velocity above 0.8 m/s. The A3 feature is dependent mainly on liquid loading and its distribution is only concentrated in the slug flow regime, which indicates that as a flow discriminating parameter, this feature will only be effective in this region. The linear prediction coefficients A4 and A5 show similar sensitivity to flow conditions and are mainly effective in the slug flow regime, particularly to the liquid phase. The linear prediction coefficient residual error, E_p displays visible dependency on gas and liquid superficial velocities as the superficial liquid velocity is increased above 0.4 m/s.

The contour plots of the line spectral frequency features of the absolute pressure signal are given in Figures 4.13a to 4.13e. The distribution maps of the first line spectral frequency (LSF1) appear to be concentrated mainly in the slug flow regime. The LSF2 and LSF3 show more sensitiveness to flow conditions in the slug and in the annular/mist flow regimes. LSF4 appears to be most effective feature having widely distributed response in all the flow regimes studies, while LSF5 seems only having some response in the slug and in upper part of the annular/mist flow regime.

Figure 4.11: Amplitude Features Distribution Maps of Absolute Pressure Signal

Figure 4.11a: AV Feature of Absolute Pressure

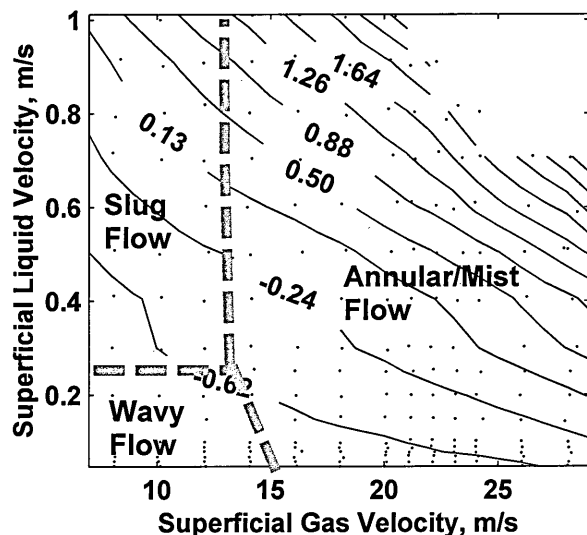


Figure 4.11b: SD Feature of Absolute Pressure

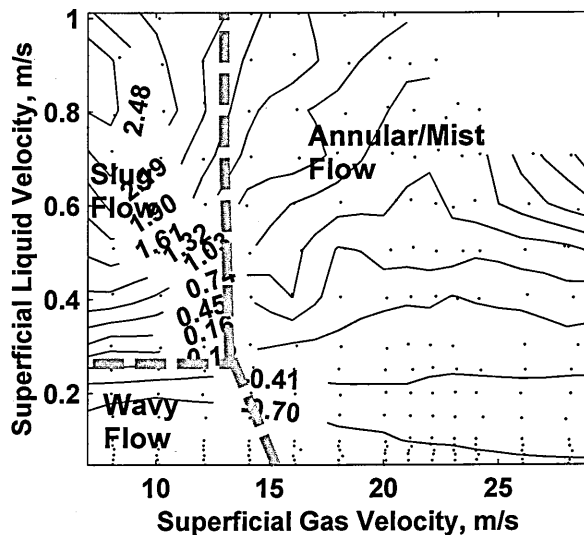


Figure 4.11c: CV Feature of Absolute Pressure

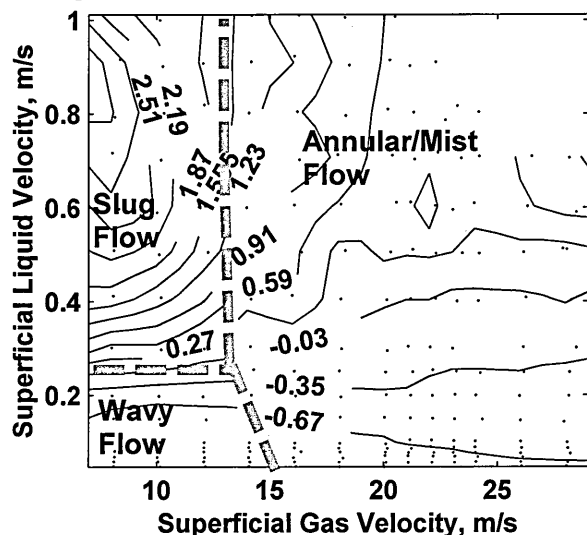


Figure 4.11d: CS Feature of Absolute Pressure

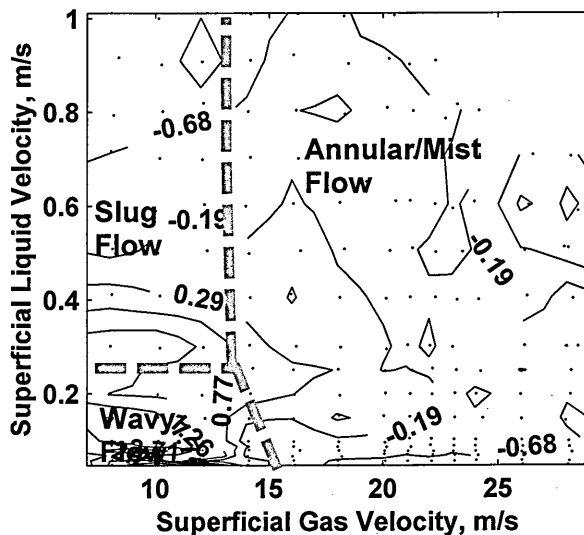


Figure 4.11e: CK Feature of Absolute Pressure

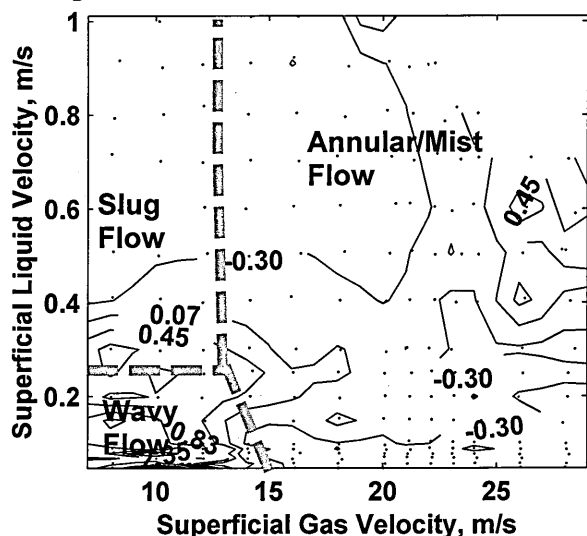


Figure 4.11f: ET Feature of Absolute Pressure

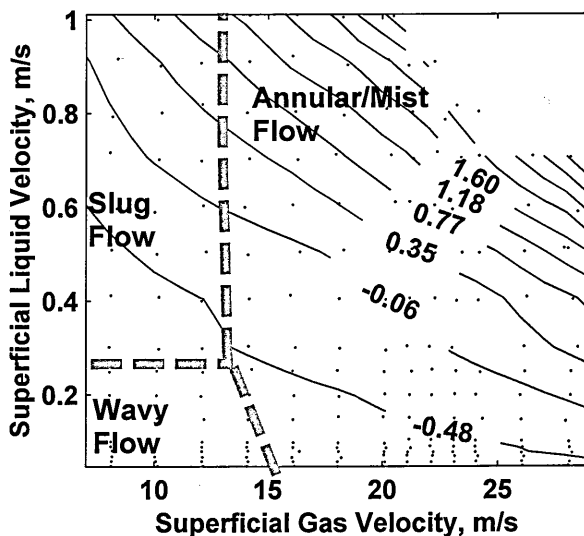


Figure 4.12: LPC Features Distribution Maps of Absolute Pressure Signal

Figure 4.12a: A1 Feature of Absolute Pressure

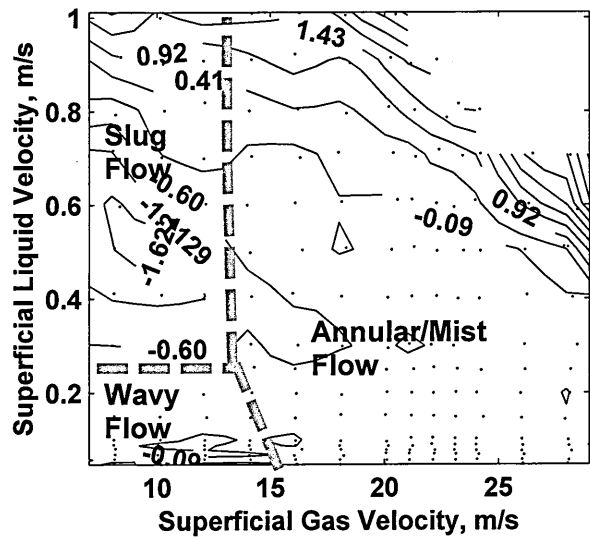


Figure 4.12b: A2 Feature of Absolute Pressure

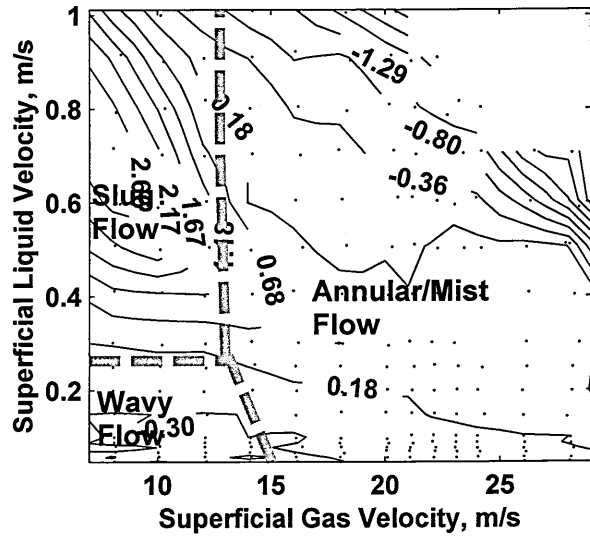


Figure 4.12c: A3 Feature of Absolute Pressure

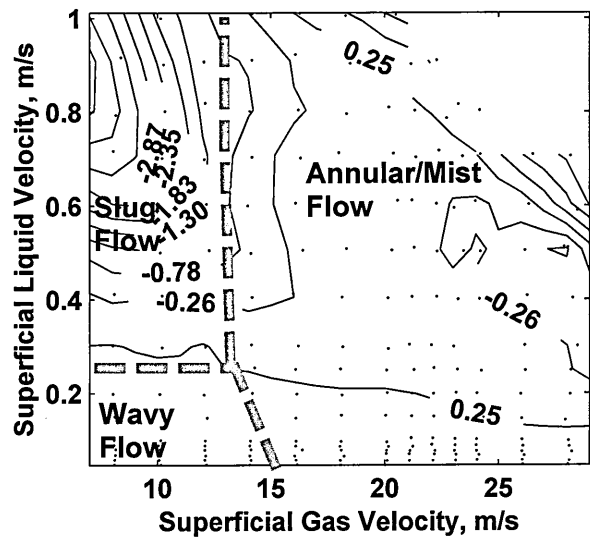


Figure 4.12d: A4 Feature of Absolute Pressure

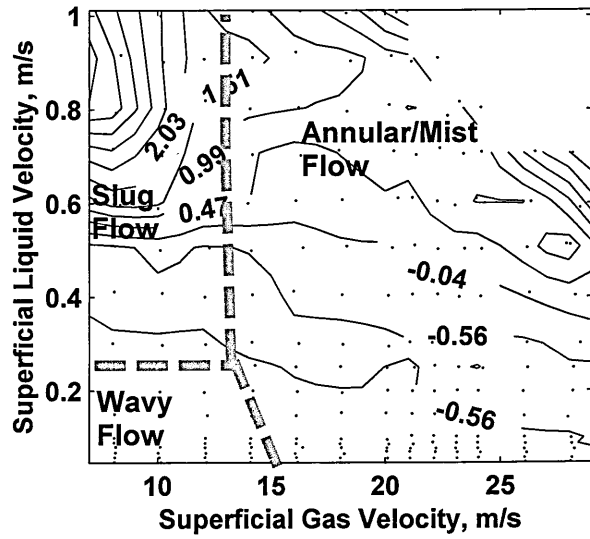


Figure 4.12e: A5 Feature of Absolute Pressure

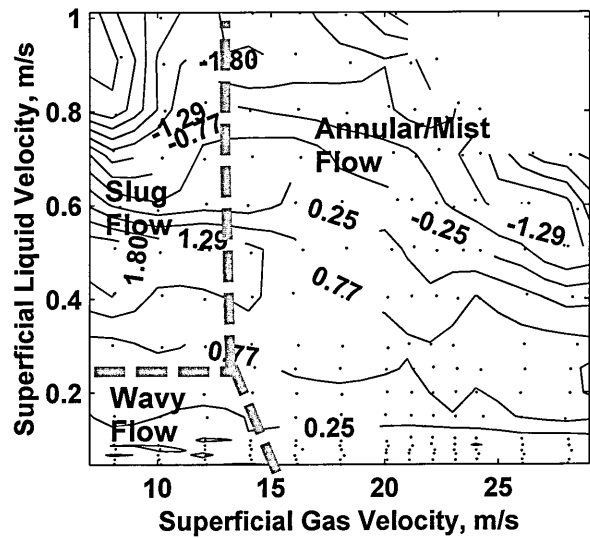


Figure 4.12f: A6 Feature of Absolute Pressure

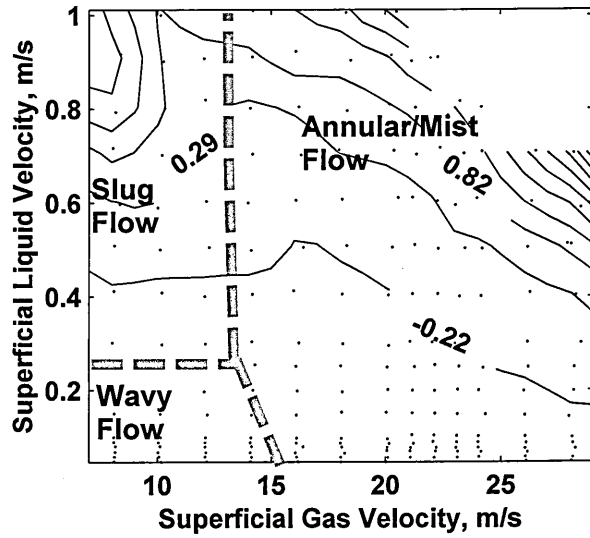


Figure 4.13: LSF Features Distribution Maps of Absolute Pressure Signal

Figure 4.13a: LSF1 Feature of Absolute Pressure

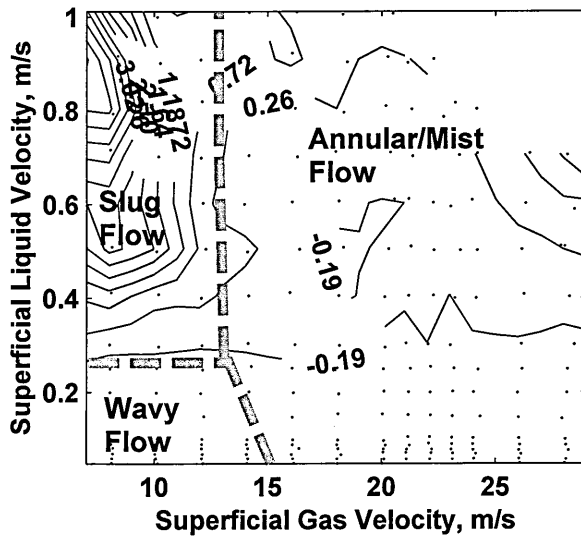


Figure 4.13b: LSF2 Feature of Absolute Pressure

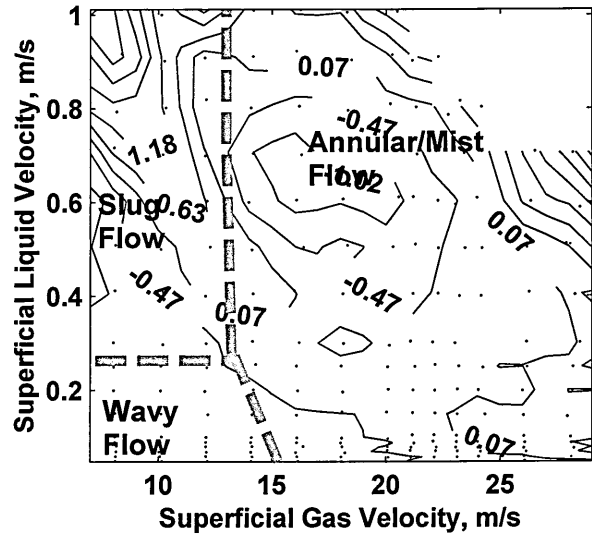


Figure 4.13c: LSF3 Feature of Absolute Pressure

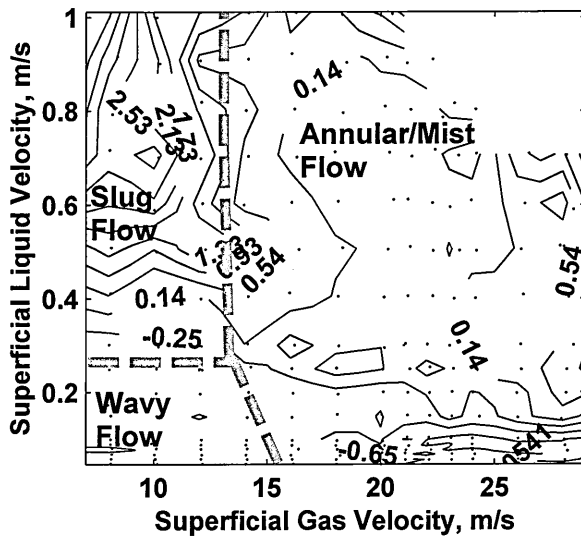


Figure 4.13d: LSF4 Feature of Absolute Pressure

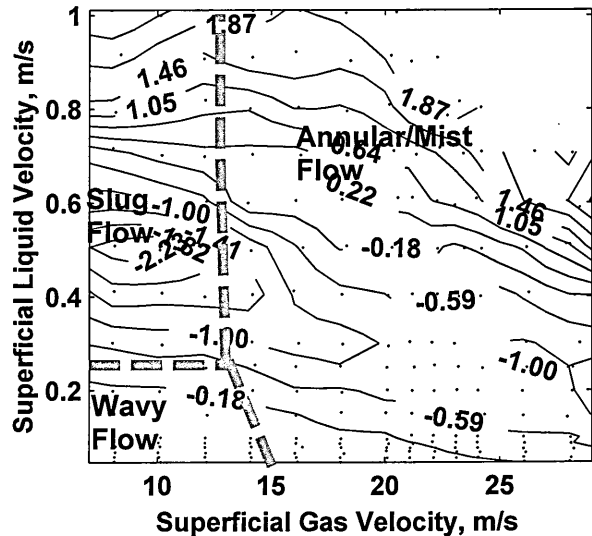
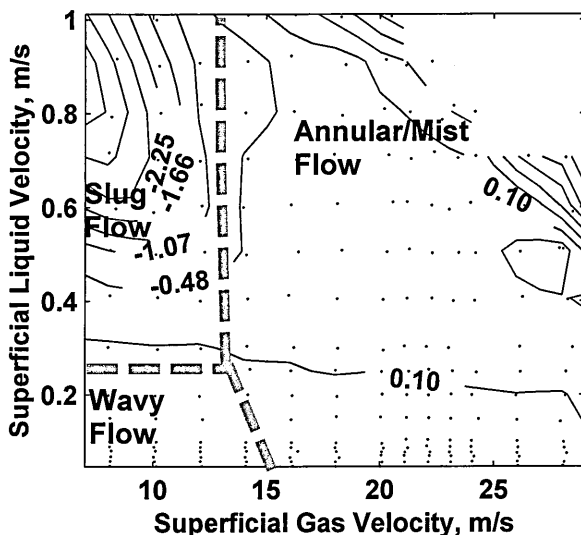


Figure 4.13e: LSF5 Feature of Absolute Pressure



4.3 Conclusions

Below are some concluding remarks that can be drawn from this chapter.

1. Two axial differential pressure sensors (DP12 and DP13) and one single-end absolute pressure sensor have been installed on a horizontally mounted Venturi meter (see Figure 3.3 for the location of pressure sensors). The test matrix covered three multiphase flow regimes (wavy, slug and annular/mist) as well as dry gas flow data, with most data gathered in the annular/mist flow regime, as it mainly characterises wet gas flow. The results presented in this chapter showed that each of the pressure sensors responds uniquely to each flow regime (Figures 4.1 to 4.3). Further analysis revealed that as certain flow parameters are varied (liquid loading and gas velocity) that each pressure sensor's response varied accordingly (Figure 4.4).
2. Stochastic features have been extracted from the pressure sensors in three information domains (amplitude, linear prediction coefficients, LPC and line spectral frequencies, LSF). Features were normalised by applying zero mean and unit-variance normalisation, which equalises the magnitude and dynamic range of each feature, so that they are given equal emphasis. Further dimensionality reduction was not found useful as it resulted in losing some of the discriminatory information present in the data and in reduced classification accuracy.
3. The feature contouring analysis showed that there is a clear relationship between stochastic features and flow parameters (superficial gas and liquid velocities). All features displayed a strong dependency on liquid loading and gas velocity. There is clear evidence from the contour plots that an input-output mapping exists between the above stochastic features and the corresponding superficial gas and liquid velocities.

4. The contour plots also revealed that the feature distributions change over different flow regimes. For example, the SD feature of all the pressure sensors significantly change trend as it goes over the wavy, slug and annular/mist flow regimes, as many other features do too. The change in feature trends is more pronounced in the slug flow regime than in the wavy and annular/mist flow regime. This could probably be due to the fact that both wavy and annular/mist flow regimes are usually considered steady state and stable flow conditions as compared to the more transient and dynamic flow condition seen with slugging conditions.
5. The observed feature behaviour indicates that if pattern recognition system is developed which is trained/calibrated upon a data (feature vectors) set gathered, say, in annular/mist flow and the system experiences a flow regime change, then the system may not be expected to perform satisfactorily. The system performance would be more drastically affected by slugging conditions than the development of wavy flow (flow regime affect is investigated in chapter 5).

The following chapter will now examine the performance of a pattern recognition for flow rate measurement that has been constructed to model the non-linear relationship between the stochastic features extracted from each pressure sensor and the individual phase flow rates. The system is being constructed and tested for its effectiveness in enabling the Venturi meter to measure the individual gas and liquid flow rates without prior knowledge of either phase.

CHAPTER 5

FLOWRATE MEASUREMENT BY BAYESIAN MLP NEURAL NETWORKS

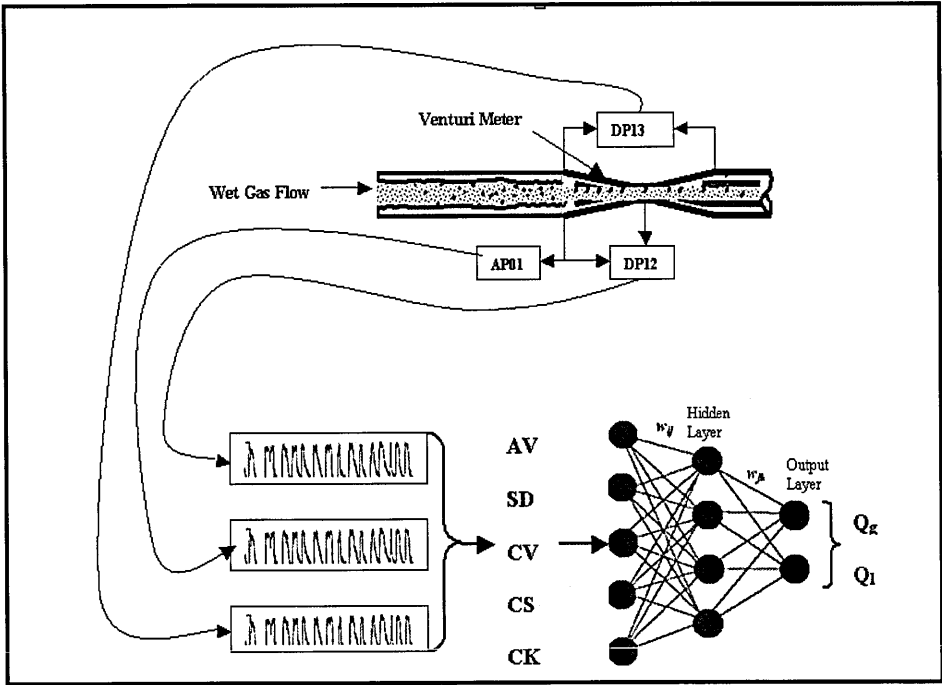
The purpose of this chapter is to detail the results obtained with the use of the Bayesian regularisation multi layer perceptron (MLP) neural networks discussed in chapter 2 and the features, identified in the previous chapter to measure the individual gas and liquid superficial velocities. The effect of flow regime and pipeline operating pressure on the pattern recognition system will also be examined.

5.1 Overview of PR Workflow and Approach to Wet Gas Metering

Once an effective number of features have been identified, the next problem to be solved is to find a mapping from these feature vectors to the superficial gas and liquid velocities (volumetric flowrates). The exact form of this mapping is to be determined from a data set of labelled examples. The results obtained from such mapping for both previously known flow conditions as well new ones is the subject for discussion in this chapter.

Figure 5.1 below is generic workflow of the main elements involved in the pattern recognition approach for wet gas flow metering as proposed in this work.

Figure 5.1: Pattern Recognition Approach to Wet Gas Flow Metering



At the outset of the pattern classification problem, the available data had to be subdivided into training and test data. Having trained the systems with some correct examples of system inputs and desired outcome, the performance of the network has to be appraised by independent test data, which has not been seen previously by the network. Out of the 272 experimental data points available, 150 were used for training and the remaining 122 for testing as shown in Figure 5.2 below.

Figure 5.2: Training (Calibration) and Test (Measurement) Data

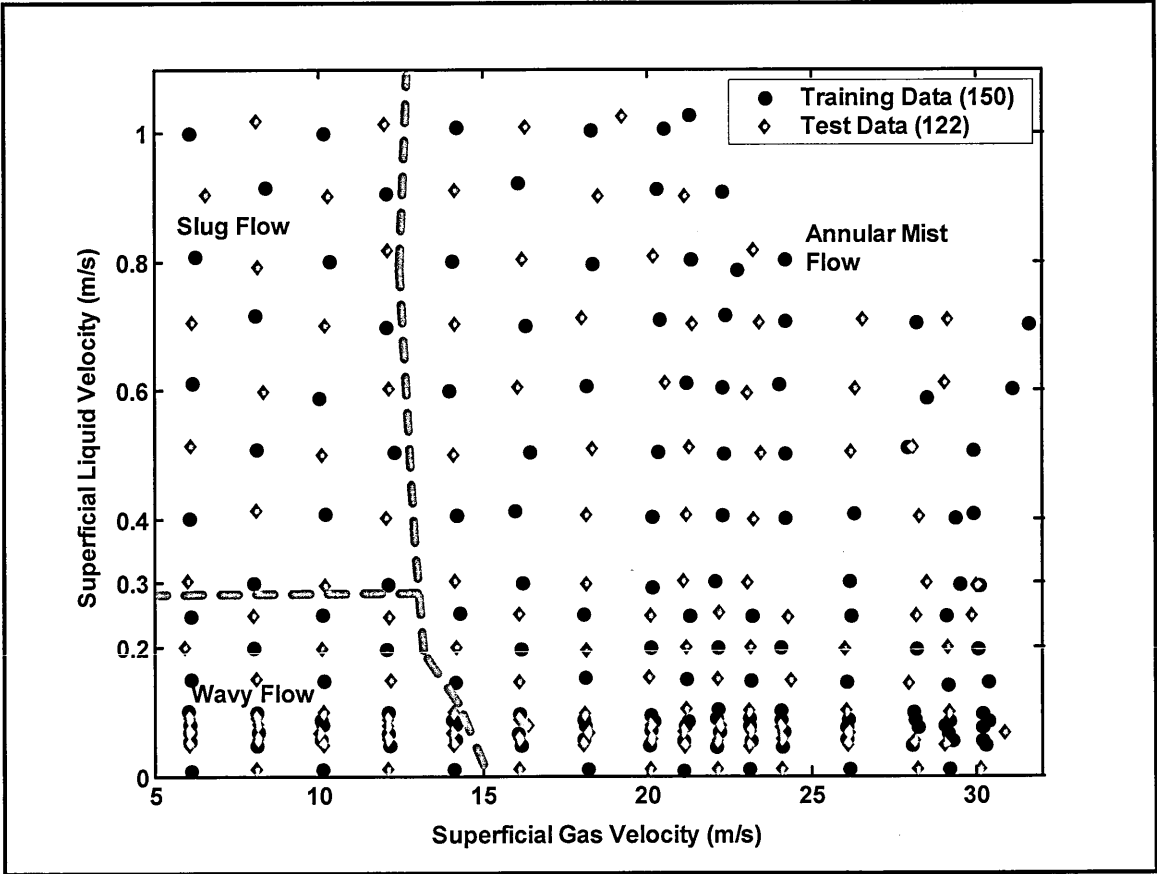
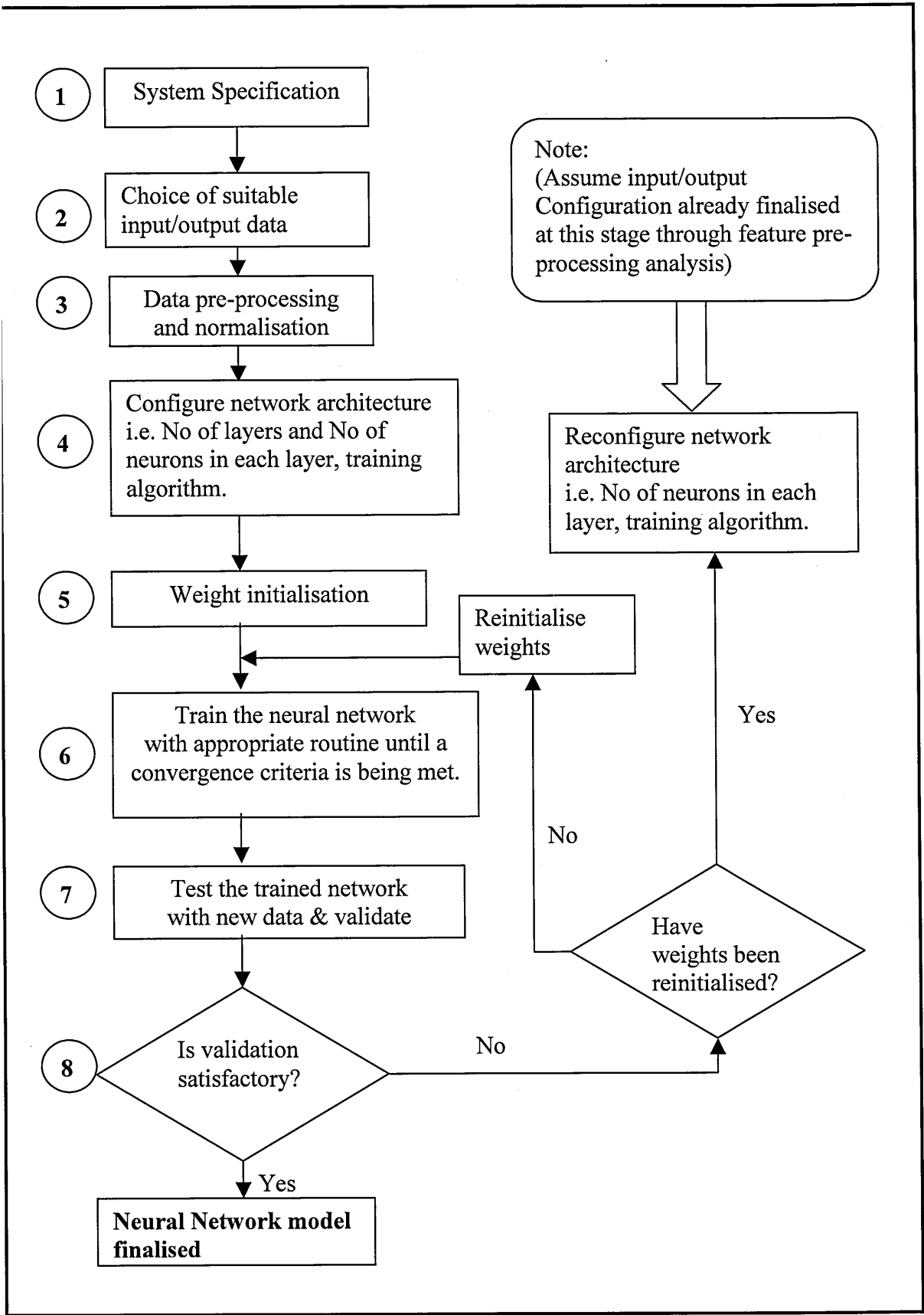


Figure 5.3 shows the system identification process, which was developed in this research to train the neural network and then test its generalisation performance with previously unseen data.

Figure 5.3: Neural network system identification steps



As was mentioned in chapter 2, a two layer Multi-Layer Perceptron (MLP) with sigmoid non-linear transfer function can approximate any function with arbitrary accuracy. To test this theory, the numbers of hidden layers were varied, including one, two and three hidden layers. It was observed that any more than one hidden layer would increase the computation time without resulting in any improvement in accuracy. Hence a two-layer (one hidden layer and one output layer) network was used throughout this study.

Choosing the number of neurons in the hidden layer depends on the complexity of the underlying function, which the MLP is attempting to approximate. Too many hidden neurons and the danger exists that the training set is simply memorised, while on the other hand a MLP with too few hidden neurons will not generalise well to new data sets. In most of the applications involving MLP, the network configuration is found by trial and error, starting with a small number of neurons and different sets of random, initial weight values. However, in this study a statistical technique known as Bayesian regularisation has been evaluated and found to successfully optimise the number of hidden neurons needed for classification in an automated manner.

Another crucial step for the successful implementation of neural network applications is the use of an appropriate training algorithm. There is vast number of algorithms available in the literature (see chapter 2) for the training MLP. Fortunately, the tedious systematic testing of a large number of training algorithms and network architectures was accomplished by the use of *Neural Network Toolbox of MATLAB*. All the training algorithms given in Table 2.2 were initially tested in this study and the Levenberg-Marquardt (LM) algorithm was found to give the best classification results. However, it was noticed that when new data, that was previously unseen by the network was introduced; the generalisation ability of this algorithm was badly affected. This problem is commonly referred to as over-fitting.

Different types of techniques have been introduced to improve generalisation to avoid the over-fitting problem. The two most widely used methods being cross-validation, otherwise known as early stopping and regularisation. Both of these techniques were

tested during the current research study. Although cross-validation was found to improve generalisation, as compared to the case of no provision for generalisation, however its performance was significantly inferior to the Bayesian regularisation technique. A contributing factor to the poor performance of the cross-validation technique could be attributed to the fact that by sub-dividing the available data into three sub-sets (training, validation and testing) it results in a reduced training set. Hence the information contained in the selected samples is not optimally used and the risk of under-constrained training increases. Furthermore the cross-validation technique involves a lot of trial and error runs to optimise the number of neurons in the hidden layer. For these reasons, the cross-validation technique was dropped in favour of the Bayesian regularisation technique for this study. The regularisation technique in combination with the Levenberg-Marquardt (LM) algorithm is implemented in MATLAB as detailed in chapter 2.

5.2 Network Training, Optimisation and CPU time

One feature of the Bayesian regularisation technique is that it provides a measure of how many network parameters (weights and biases) are being effectively used by the network. As seen in Figure 5.4, the final trained network uses approximately 126 parameters out of 152 total weights and biases in the 12-10-2 network (i.e. 12 input nodes from amplitude feature vectors, 10 neurons in the hidden layer and two neurons in the output layer), as shown in Figure 5.4. This effective number of parameters should remain approximately the same, no matter how large the total number of parameters in the network becomes. (This assumes that the network has been trained for a sufficient number of iterations (epochs) to ensure convergence).

It is clear that the algorithm has truly converged if the sum squared error (SSE) and sum squared weights (SSW) are relatively constant over several iterations, which is true in this case as shown in figures 5.4a and 5.4b respectively. When this occurs, a decision may be made to terminate the training and retain the weights and biases for network testing.

Before the network is tested on new and previously unseen data it is important to examine the performance of the network on its calibration database (i.e. test the network on the same data that it being trained with) in order to evaluate the network's *repeatability* capability. It is only when the network's *repeatability* accuracy is satisfactory that the use of the network for measurement of new data should be considered. Figure 5.5 shows the *repeatability* performance of the MLP trained with the 18 amplitude features extracted from all the three sensors. The plots are a linear regression fit between the experimentally measured velocities and the MLP prediction results. The linear regression fit shows that the network achieves excellent repeatability results and therefore it can now be used for measurement of previously unseen data.

Testing the different neural network architectures was done using an Intel Pentium 3 with CPU (central processing unit) of 1200Mhz and 260 KB RAM. When the maximum numbers of in put feature vectors were used the CPU time required was about ½ hour and the training process varied between 120- 1700 epochs (cycles) depending on which feature vectors used. The Levenberg-Marquardt training algorithm was used throughout the different runs.

Figure 5.4: Training the Bayesian MLP Neural Network

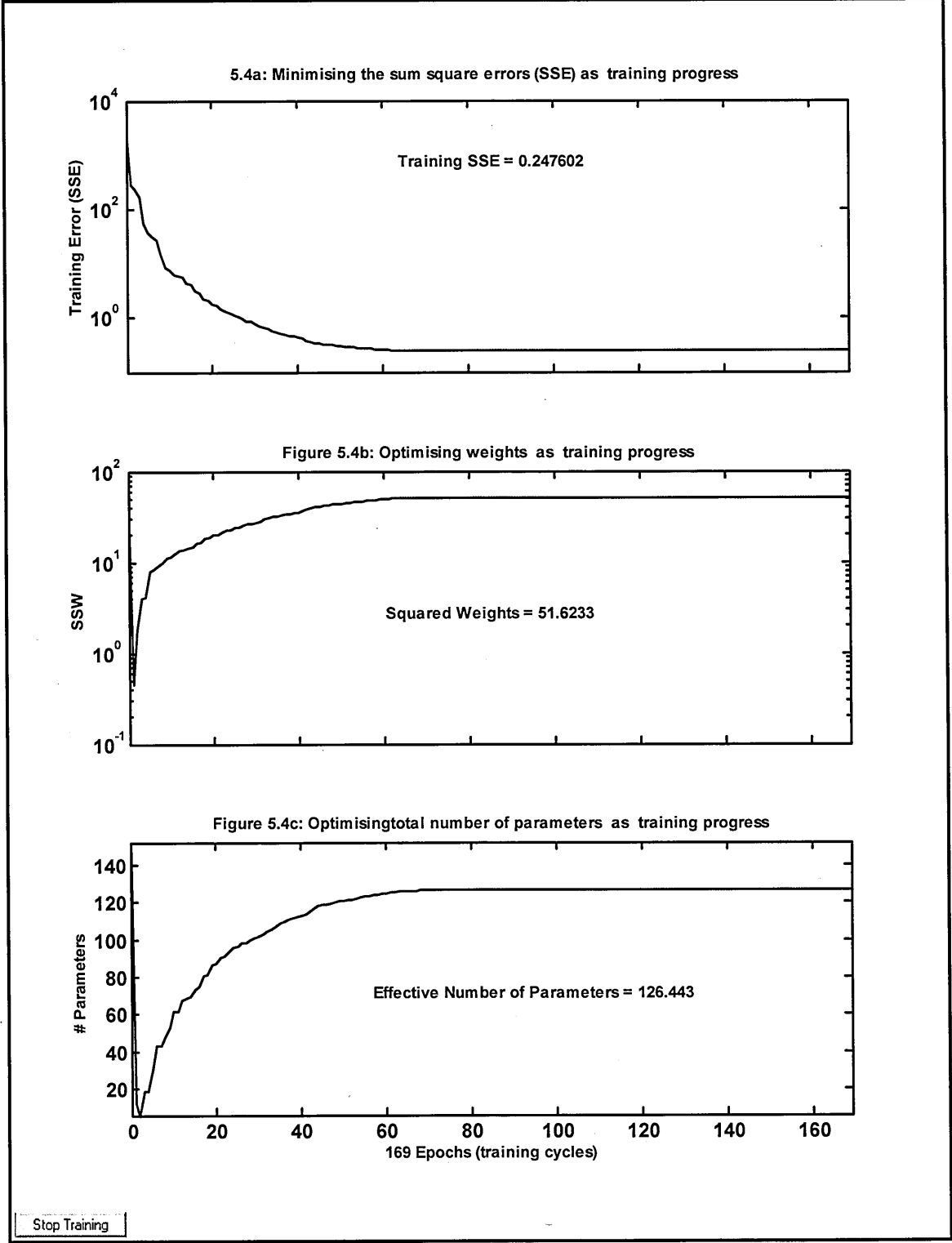
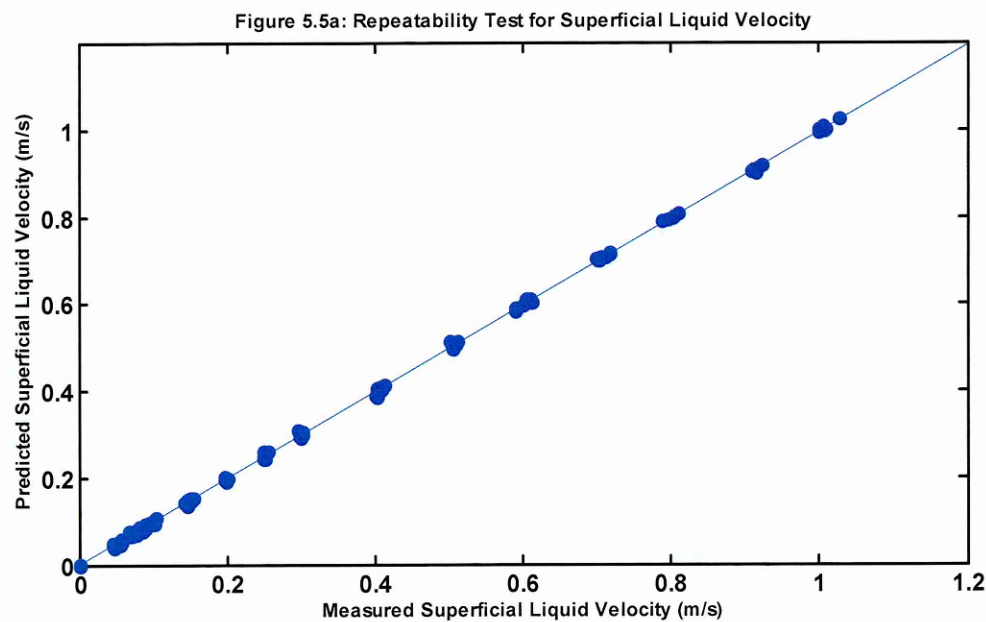
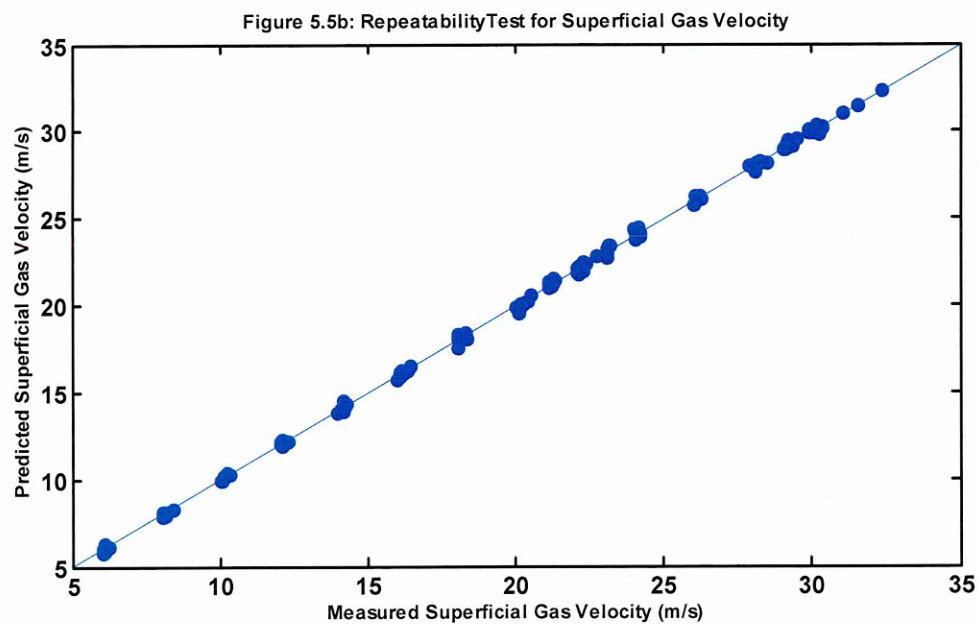


Figure 5.5: Repeatability Test of Bayesian MLP Neural Network



5.3 Final Network Architecture

Based on the above *repeatability* tests, a network with architecture of the form $(m - 10 - 2)$ was kept constant throughout this study, where the only variable is m , which is the input feature vectors.

The following sections will now examine the *reproducibility* performance of the above network by using different feature vectors for the measurement of gas and liquid flow rates.

5.4 Flow Rate Measurement

As a result of extensive data analysis carried during the course of this study, it was learnt that there are many different ways to construct feature combinations to form feature vectors. Initially a ‘leave-one-out’ technique was used as a feature combination technique. In this technique, all of the training feature vectors except one are used for estimating the network parameters (weights and biases) using the Bayesian MLP neural network classifier. However this is a tedious and iterative process that is completed when all the individual features in the data have been removed and then introduced, with cross-domain features also considered. Results indicated that the network classification accuracy improved with increased feature vectors. A better and more efficient method of constructing a feature vectors was found by combining the features of each information domain as shown in Table 5.1. This will also provide a systematic methodology of comparing the discriminatory ability of different information domains. This procedure was repeated for each pressure sensor. The flow rate measurement results obtained from each pressure sensor will now presented below. In this work a measurement is considered successful if it falls within $\pm 5\%$ relative measurement error band (as calculated by equation 2.42).

Table 5.1: Input Feature Vectors for Flow Rate Measurements

NO	Feature Domain	Training Data	Test Data
1	Amplitude Features	6×150	6×122
2	Linear Prediction Coefficients (LPC)	6×150	6×122
3	Line Spectral Frequencies (LSF)	5×150	5×122
4	Amplitude +LPC +LSF	17×150	17×122

5.4.1 Venturi Throat DP (DP12) Flow Rate Measurement Results

The flow rate measurement results for the throat DP are discussed below (see Figure 3.3 for the location of the different pressure sensors). The results obtained using the amplitude feature vectors will be presented first, followed by the linear prediction results and finally the line spectral frequency.

The predictions of the liquid and gas superficial velocities were made for each information domain using the features shown in Table 4.1 and combined as shown in Table 5.1. Two subset plots are used for the visualisation of the network classification results. The first subset plots the measurement errors as a function of gas volume fraction (GVF). The second is a plot of the actual test matrix (used for testing the network) with superficial gas velocity on the x-axis and superficial liquid velocity on the y-axis. The visually observed flow regime boundaries are also plotted on this figure. The data points with higher measurement errors are also labelled on the second subset figure for better visualisation of the exact location of these higher error data points.

Figure 5.14 contains a summary of the flow rate measurement performance by different feature vectors of the throat DP, so if the reader prefers to skip the following detail discussions regarding the performance of each information domain, they can refer to this figure for a summary of the results.

In terms of the amplitude domain results, the measurement errors as a function of gas volume fraction (GVF) for the liquid phase are shown in Figures 5.6a and 5.6b. As can be seen in Figure 5.6b, four flow regimes were investigated here (dry gas, wavy flow, slug flow and annular mist flow regimes). In the dry gas conditions, the network was trained with zero superficial liquid velocities as well as dry gas data, so that the network's ability in predicting liquid presence can be simulated.

It can be seen that the amplitude features of the throat DP perform well on dry gas conditions as well as wavy and slug flow regimes, where the measurement errors are

within a $\pm 5\%$ error band. Measurement errors of within $\pm 5\%$ are also obtained in the annular flow regime (below 0.2 m/s liquid velocity. The main reason for the higher errors in the area of superficial liquid velocity higher than 0.2 m/s may be due to the fact that the available data is coarser in this region than it is for the area below this value.

Figure 5.7a and 5.7b illustrate the measurement results obtained on the gas phase. Similar to the liquid phase, 100% of the test points are measured to within $\pm 5\%$ error band in dry gas. The higher measurement errors on the gas phase are also found mainly in the annular mist flow regimes, particularly above superficial liquid velocity of 0.2 m/s.

The measurement error distributions of the linear prediction coefficients (LPC) are shown in Figures 5.8a to 5.9b. It can be seen that the LPC features as compared to the amplitude features obtain higher measurement errors. The network also appears to achieve high measurement errors in the wavy and in the slug flow regimes, when using LPC features as training and test data. Figure 5.9a and 5.9b display the measurement error distribution on the gas phase. It is clear from these figures that significantly higher measurement errors are obtained on the gas velocity predictions as compared to the liquid phase. Furthermore, most of the higher measurement errors are found on the edges of the coarser part of the test matrix, which corresponds to the upper part (above 0.4 m/s liquid velocity) and the slug flow regimes. This trend is true of all the different feature domains used here and ascertain that pattern recognition techniques perform best when they are in interpolation mode than extrapolation.

Figures 5.10a to 5.11b show the measurement error distribution of the line spectral frequency features. The liquid phase error distribution and the location of the higher errors (i.e. $> \pm 5\%$) are displayed in Figures 5.10a and 5.10b respectively. The general performance trend is similar to that displayed by the LPC features. However, the higher measurement errors obtained by the LPC appear to be concentrated in the upper portion of the annular mist flow regime, whereas the LSF shows a measurement improvement in this area.

Figures 5.11a and 5.11b display the measurement error distribution of the LSF features on the gas velocity. When compared to the performance of the LPC features, the LSF features achieve marked improvement in the slug and annular mist flow regime, but significantly less than the amplitude features.

The contrast in measurement error distribution obtained by different feature vectors is indicative of the fact that different features respond differently to the same flow condition (see chapter 4) and therefore their combination should lead to better measurement accuracies. The performance of the throat DP feature fusion (i.e. the fusion of amplitude, LPC and LSF) has been investigated in this study.

As the foregoing trends in feature performance indicated, a much-improved measurement is obtained with amplitude feature fusion for the liquid velocity (Figures 5.12a and 5.12b). Similarly the measurement performance on the gas phase is also improved with feature fusion (Figures 5.13a and 5.13b). It is however, critical to analyse which flow regimes these improved measurement accuracies are more applicable. To compare the percentage measurement accuracy gained by the different feature vectors, the reader is referred to Figures 5.14a and 5.14b. On the x-axis of this Figure are the feature vectors and on the y-axis the percentage accuracy of each flow regime achieved within ± 5 % error band.

For the detection of the presence of liquid, the amplitude, the LSF and the feature fusion cases all obtain 100% measurement accuracy (Figure 5.14a). All the feature vectors do well on the wavy flow regime with measurement accuracies of (87, 85, 81 and 94 % respectively). The amplitude feature vectors do particularly better in the slug flow regime with 100 % of the test data measured to within ± 5 % error band, whereas the LPC feature vectors achieve the worst measurement accuracy in the slug flow with 43% accuracy. The annular mist flow regime receives comparatively closer measurement accuracy by the different feature vectors with around 80% measurement accuracy on the liquid phase.

The performance of different feature vectors is clearly different on the gas phase. Overall the amplitude feature vectors perform the best with 100% measurement accuracy in the dry gas flow rates and over 80% in all the other flow regimes. It is interesting to see that feature vector 4, which represent the feature fusion case, performs poorly on the gas velocity measurement in the slug flow regime with 39 % measurement accuracy. This indicates that the intuitive approach of ‘bigger the feature dimension the better the pattern classifier’ accuracy does hold true here. These results show generally when comparing the measurement accuracy obtained by different feature vectors, the amplitude feature vectors perform best for both liquid and gas velocity measurements in the different flow regimes.

From the above discussion, it may be concluded that if only the differential pressure sensor across the Venturi throat is available, then amplitude feature vectors should be used for the liquid and gas volumetric measurements. This also underlines the fact that neural network generalisation performance is heavily influenced by the type of feature vectors used and that the formation of a large calibration database in terms of feature vectors does not necessarily lead to improved measurement accuracy in all flow regimes. Furthermore it can be deduced from the above results that when developing a measurement system for wet gas flow (annular mist flow regime), the neighbouring flow regimes should also be considered at design stage as the measurement system will be significantly effected by the surrounding flow regimes, which can instantaneously develop at anytime in the production system.

Figure 5.6: Liquid Error Distribution from Amplitude Features of Throat DP

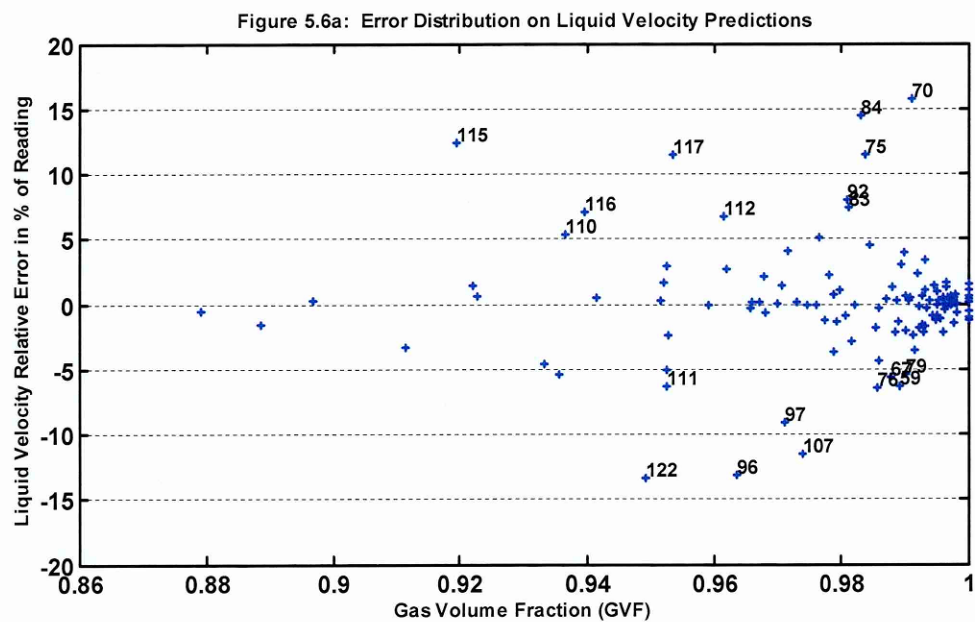
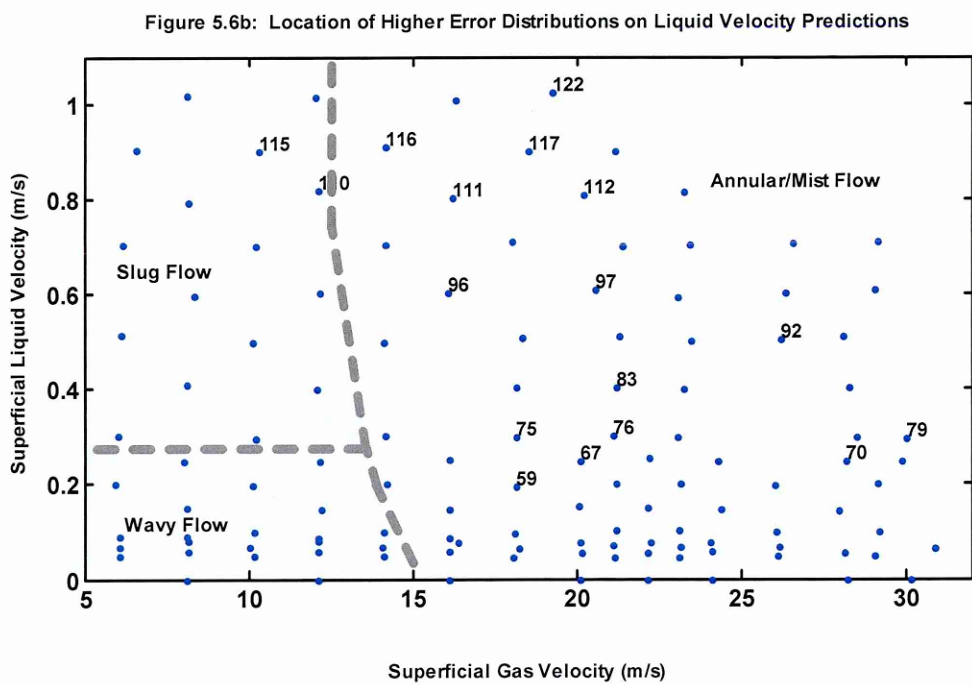


Figure 5.7: Gas Error Distribution from Amplitude Features of Throat DP

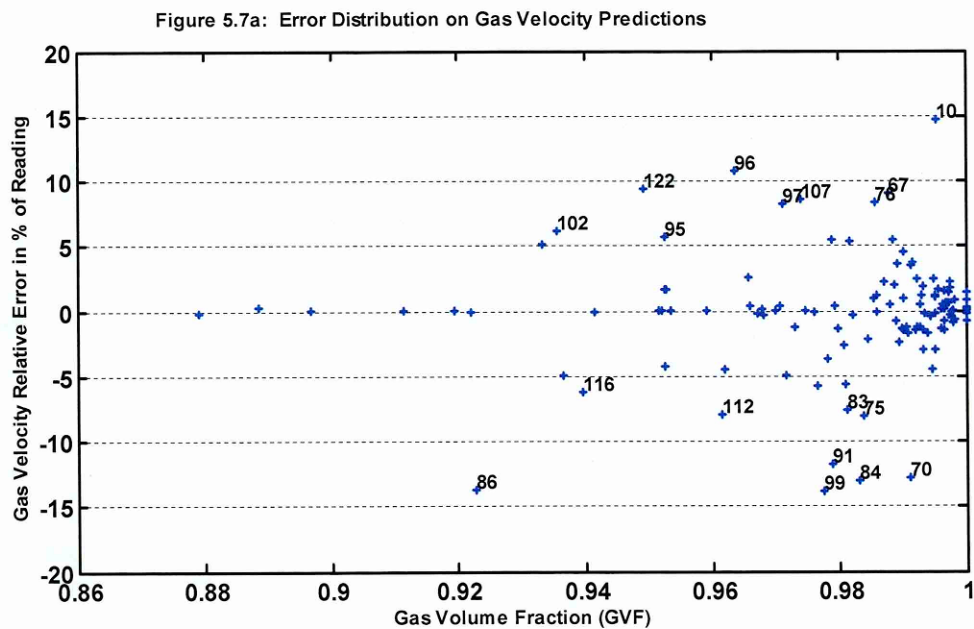
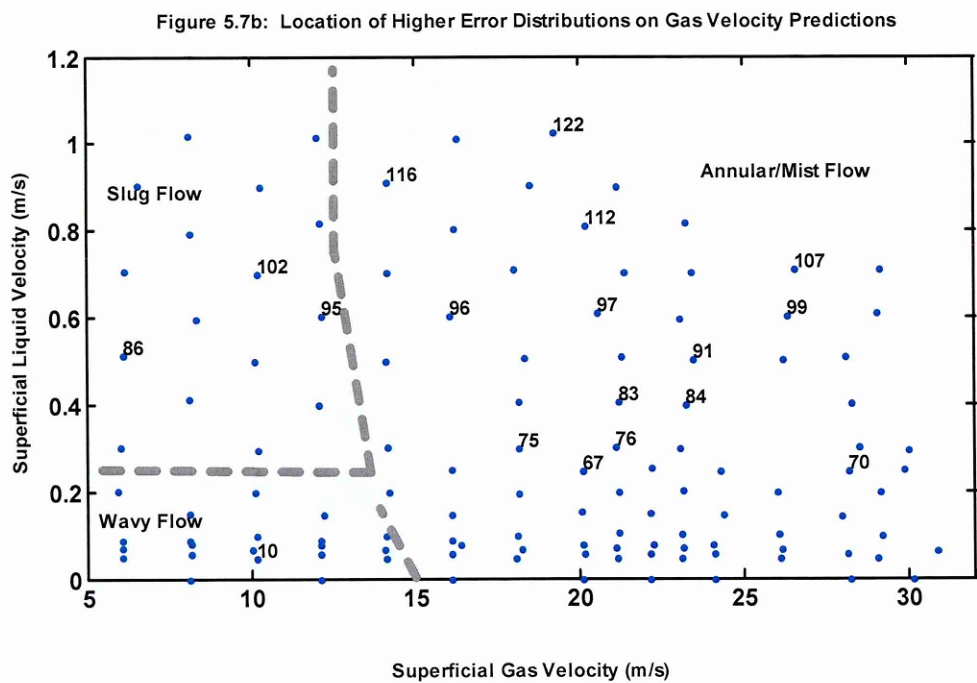


Figure 5.8a: Error Distribution on Liquid Velocity Predictions

Figure 5.8b: Location of Higher Error Distributions on Liquid Velocity Predictions

Figure 5.9: Gas Error Distribution from LPC Features of Throat DP

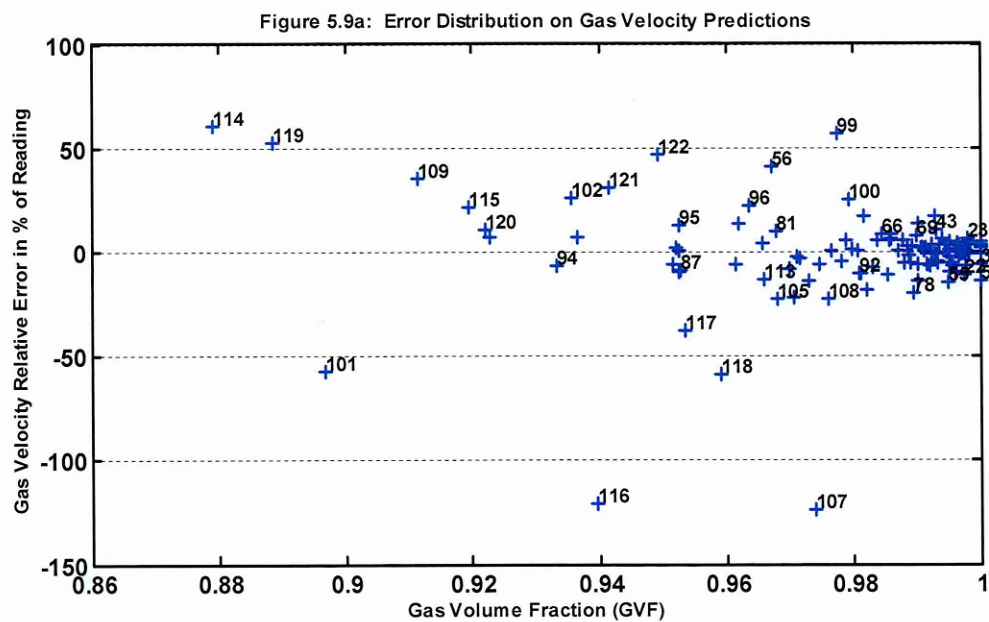
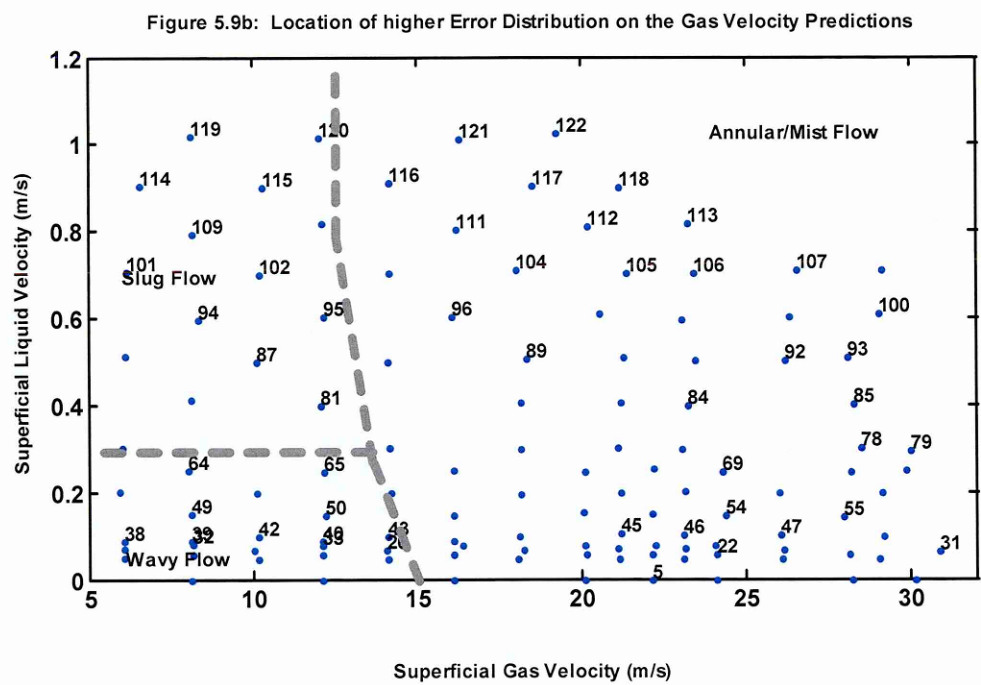


Figure 5.10: Liquid Error Distribution from LSF Features of Throat DP

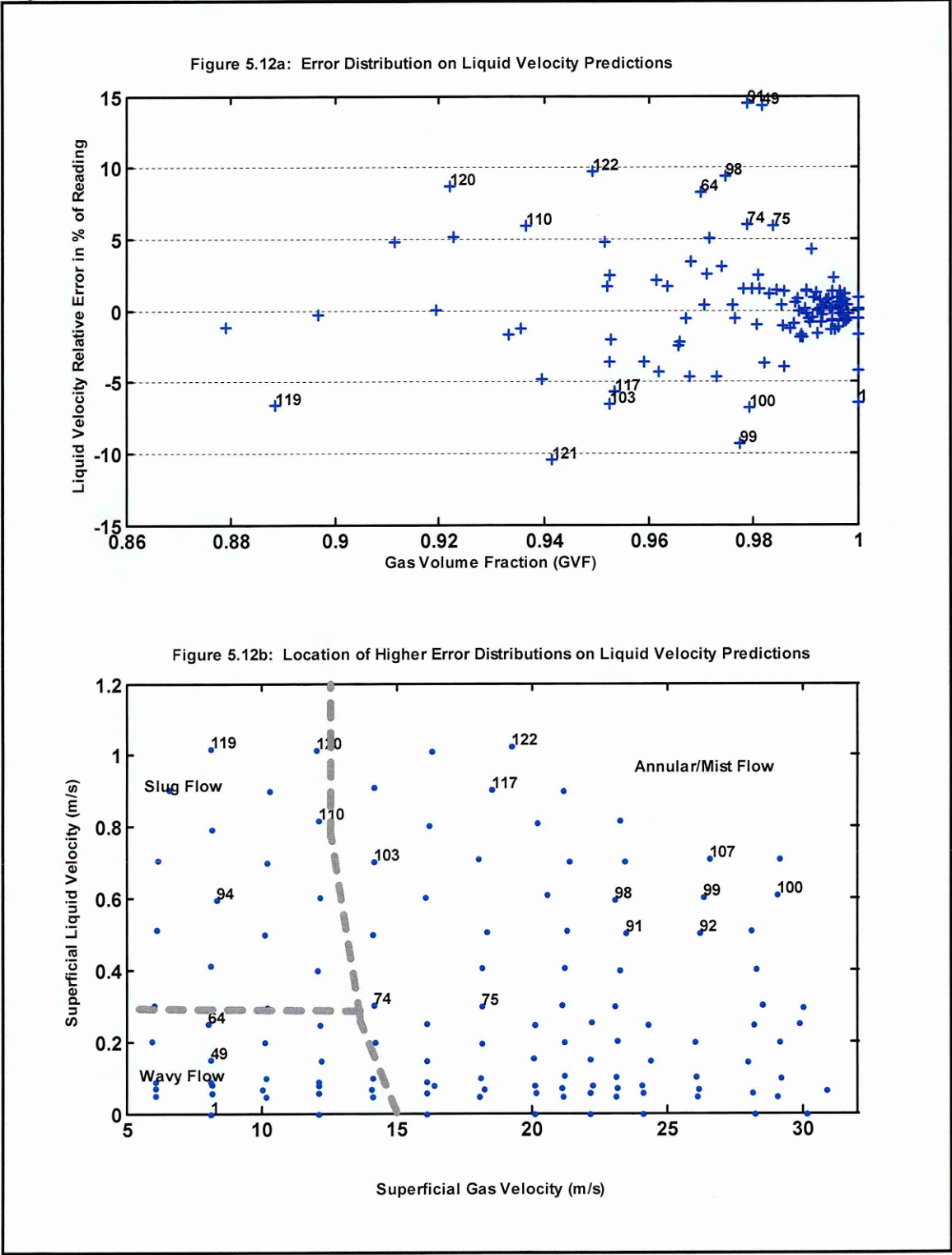


Figure 5.11a: Error Distribution on Gas Velocity Predictions

Y-axis: Gas Velocity Relative Error in % of Reading (-20 to 20)

X-axis: Gas Volume Fraction (GVF) (0.88 to 1.0)

Figure 5.11b: Location of Higher Error Distributions on Gas Velocity Predictions. A scatter plot showing Superficial Liquid Velocity (m/s) (Y-axis, 0 to 1.2) versus Superficial Gas Velocity (m/s) (X-axis, 5 to 30). Data points are blue dots, many labeled with numbers (e.g., 86, 94, 72, 104, 64, 92, 67, 42, 18, 19, 75, 77, 51, 40, 76, 65, 82, 113, 97, 68, 78, 25, 35, 22, 45, 55, 32, 43, 23, 15). The plot is divided into regions: Slug Flow (top left), Wavy Flow (bottom left), and Annular/Mist Flow (top right). A dashed line separates the Slug/Wavy Flow region from the Annular/Mist Flow region.

Figure 5.11b: Location of Higher Error Distributions on Gas Velocity Predictions

Y-axis: Superficial Liquid Velocity (m/s) (0 to 1.2)

X-axis: Superficial Gas Velocity (m/s) (5 to 30)

Regions: Slug Flow, Wavy Flow, Annular/Mist Flow

Figure 5.12: Liquid Error Distribution from Feature Fusion of Throat DP

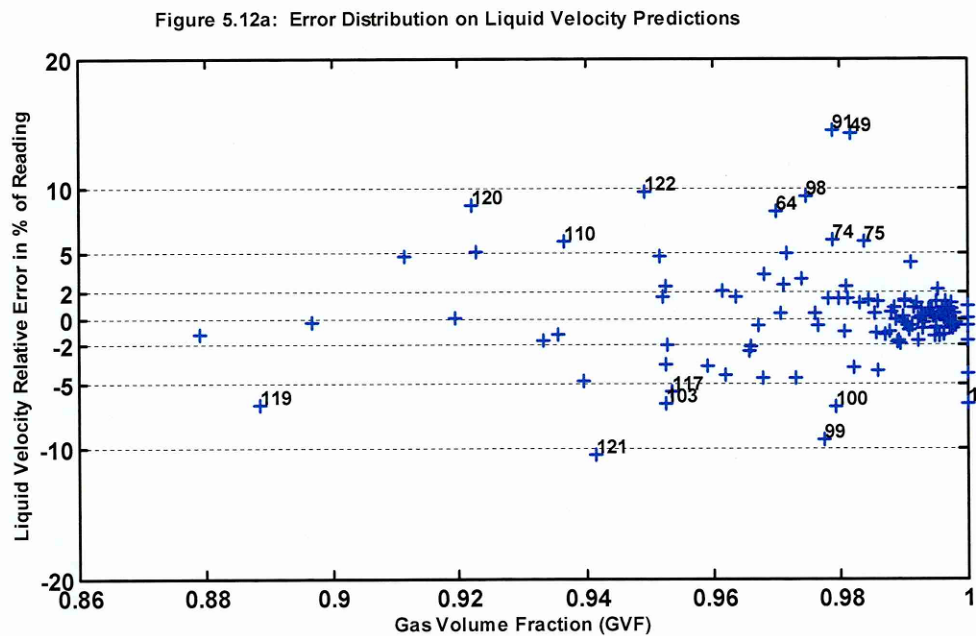
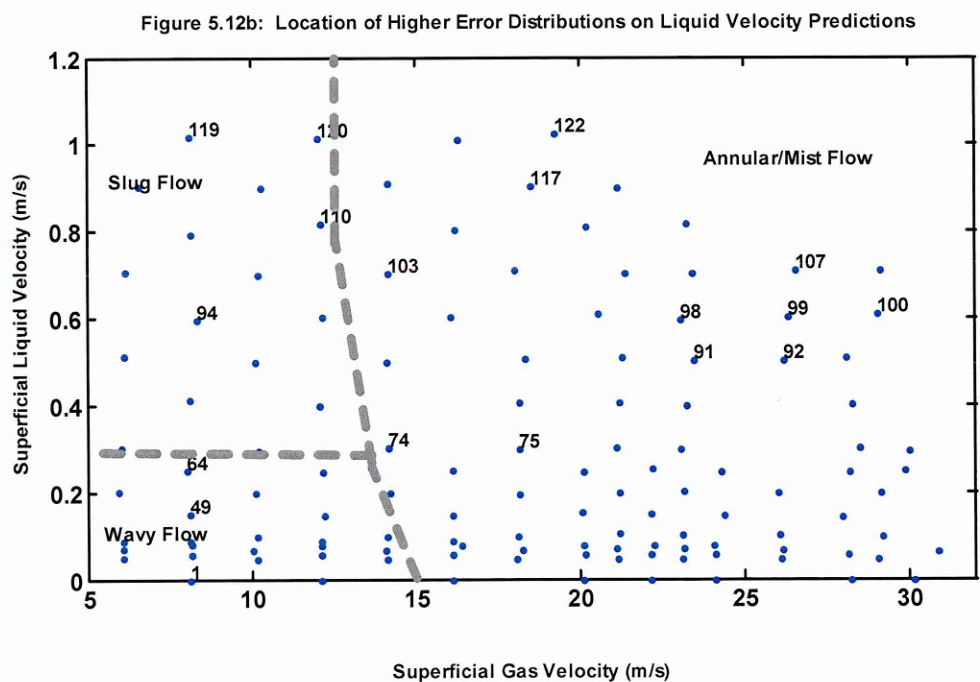


Figure 5.13: Gas Error Distribution from Feature Fusion of Throat DP

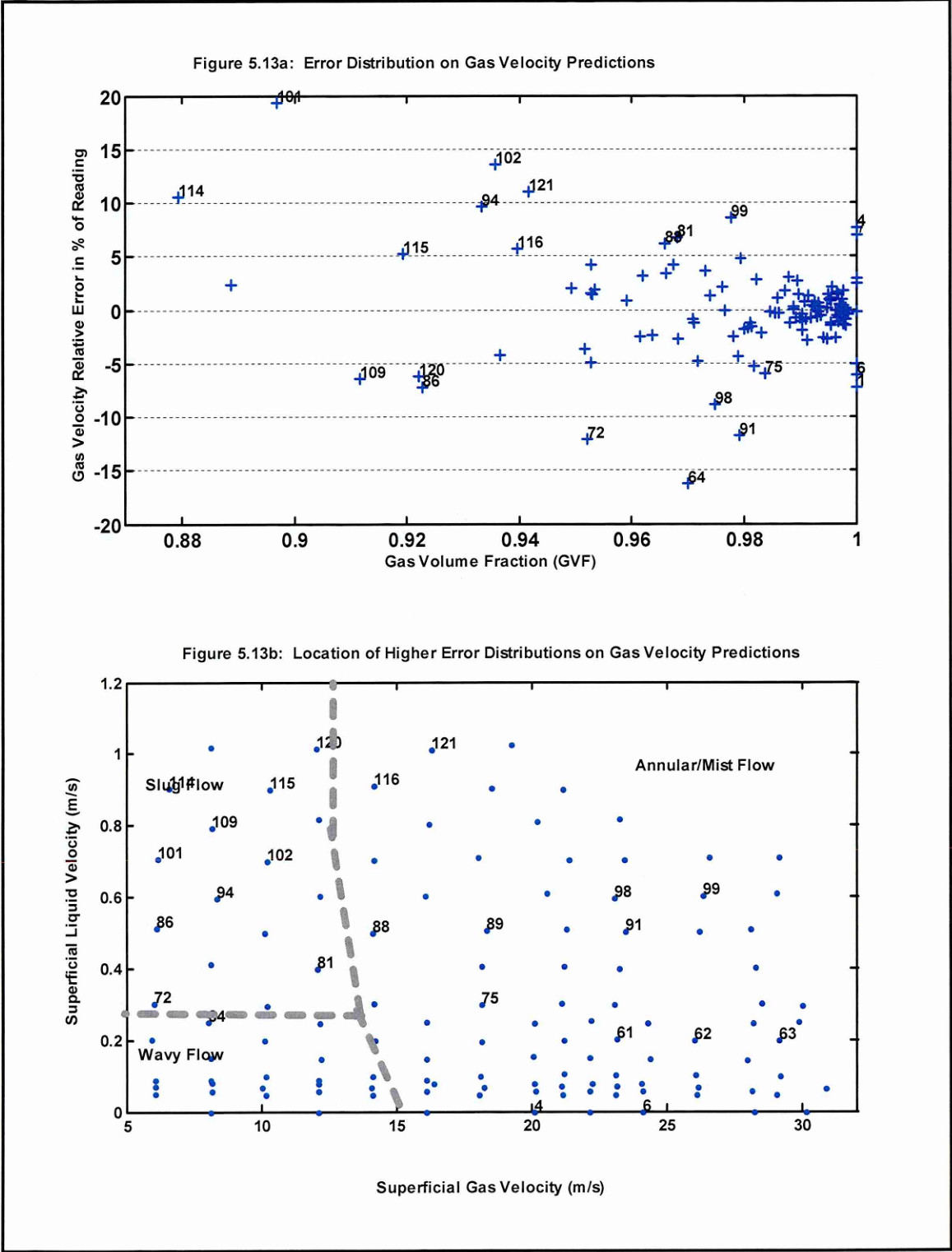
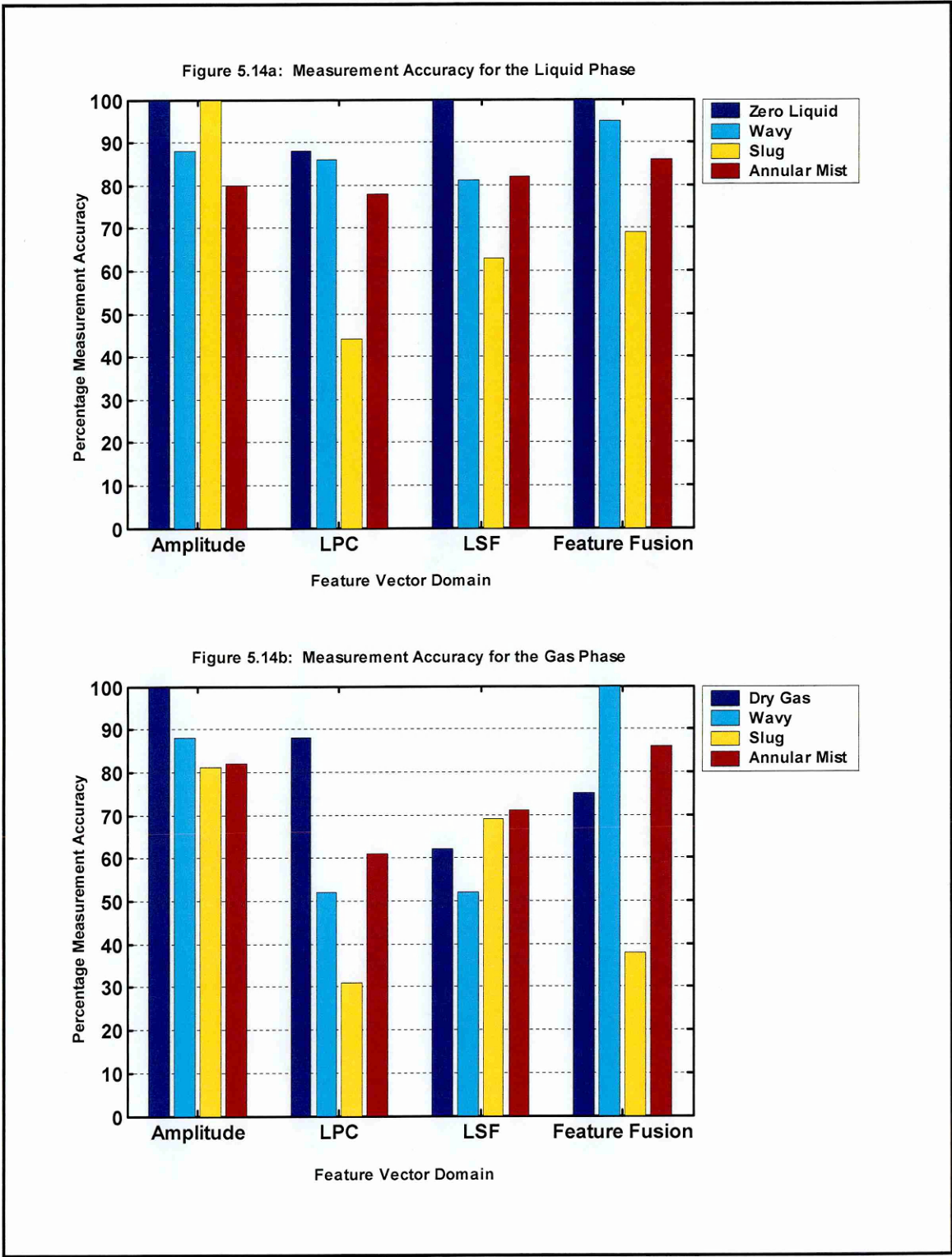


Figure 5.14: Summary of Measurement Accuracy of the Throat DP



5.4.2 Venturi Recovery Length DP (DP13) Flow Rate Measurement Results

The liquid and gas velocity measurements were made for the recovery DP signals using the three feature vectors (amplitude, LPC, LSF) as well as feature fusion. The network architecture has been kept constant with the only variable being the input feature vectors.

The flow rate measurement results obtained by the amplitude feature vectors are shown in Figures 5.15a to 5.16b. The amplitude feature vectors appear to achieve good results on the liquid velocity measurements below 0.2 m/s. Figure 5.15b shows the exact locations of those points with measurement errors greater than ± 5 % error band. The general performance trend is quite similar to that obtained with amplitude features from the throat DP, except that the throat DP performed markedly better in slug flow than the recovery DP, which could be due to the fact that throat DP readings are less effected by the instantaneous pressure transients in the slug flow regime than the recovery DP. Much better results are obtained in gas velocity predictions than the liquid velocity, especially in the slug flow (Figures 5.16a and 5.16b).

As can be seen in Figure 5.17a, the amplitude feature vectors and the linear prediction coefficients perform well in the detection of liquid presence with 100 % of test points measured to within ± 5 % error band. The feature fusion case achieves the best measurement results in wavy flow with 95 % accuracy, whereas the LPC and LSF feature vectors obtained highest measurement accuracies (both achieving 75 %) in the slug flow regime. The measurement accuracies on the annular mist flow regime by the four different feature vectors appear to closely match, with 78, 82, 83 and 75 % respectively.

Figure 5.17b shows the measurement accuracies obtained on the gas velocity predictions. The accuracies achieved by the four feature vectors on the dry gas flow rates are 75, 86, 75 and 88% respectively. On the wavy and slug flow regimes, it can be seen that amplitude feature vectors achieve the best performance with a measurement accuracy of 87 and 100% respectively. The amplitude, LPC and LSF feature vectors obtain almost

similar accuracies on the annular mist flow regime, whereas the feature vector fusion case achieves the least percentage accuracy with 62 %.

As was the case with throat DP results, the four respective feature vectors of the recovery DP also achieve varying degrees of accuracies in the different flow regimes. It is particularly interesting to note that in general, the feature vectors of the recovery DP achieve slightly better results in gas flow measurements than the throat DP, which could be because the recovery length differential pressure will naturally be better placed to pick up pressure response created by the lighter gas phase following in the upper part of the horizontally installed pipe. Having said this, the recovery DP also equally produces good results for the liquid phase, which is indicative of its sensitivity to pressure waves generated by the hydrodynamic variations within the flow.

It is this variation in accuracy that needs to be analysed when selecting the best feature vectors for flow rate measurements as no single feature vector outperforms the rest in all the different flow regimes. These results, together with the previous results of the throat DP suggest that in addition to feature fusion, the performance of fusing different sensors should also be studied (this will be analysed under section 5.4.5 below).

Figure 5.15: Liquid Error Distribution from Amplitude Features of Recovery DP

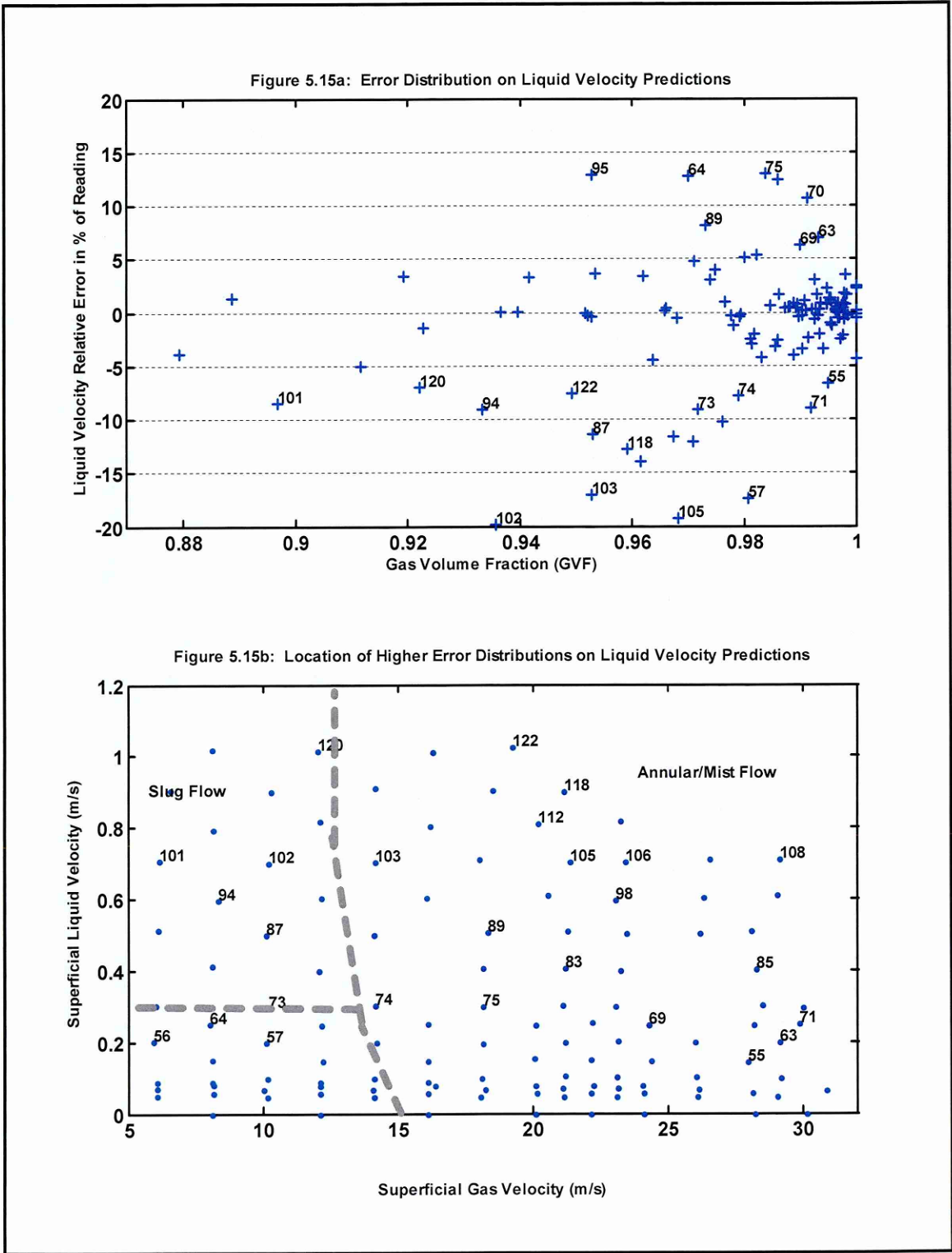


Figure 5.16: Gas Error Distribution from Amplitude Features of Recovery DP

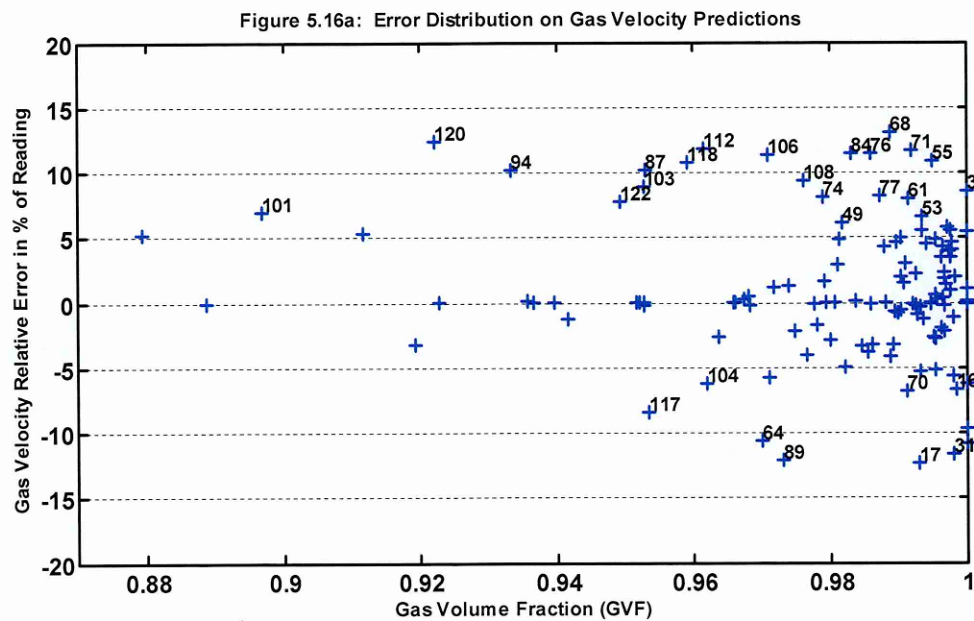
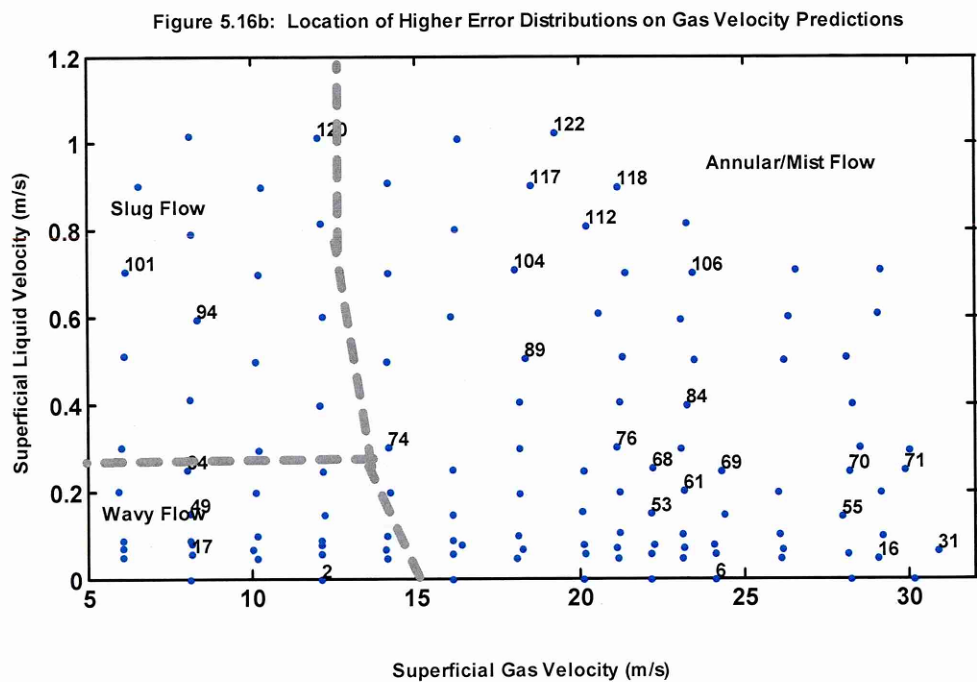
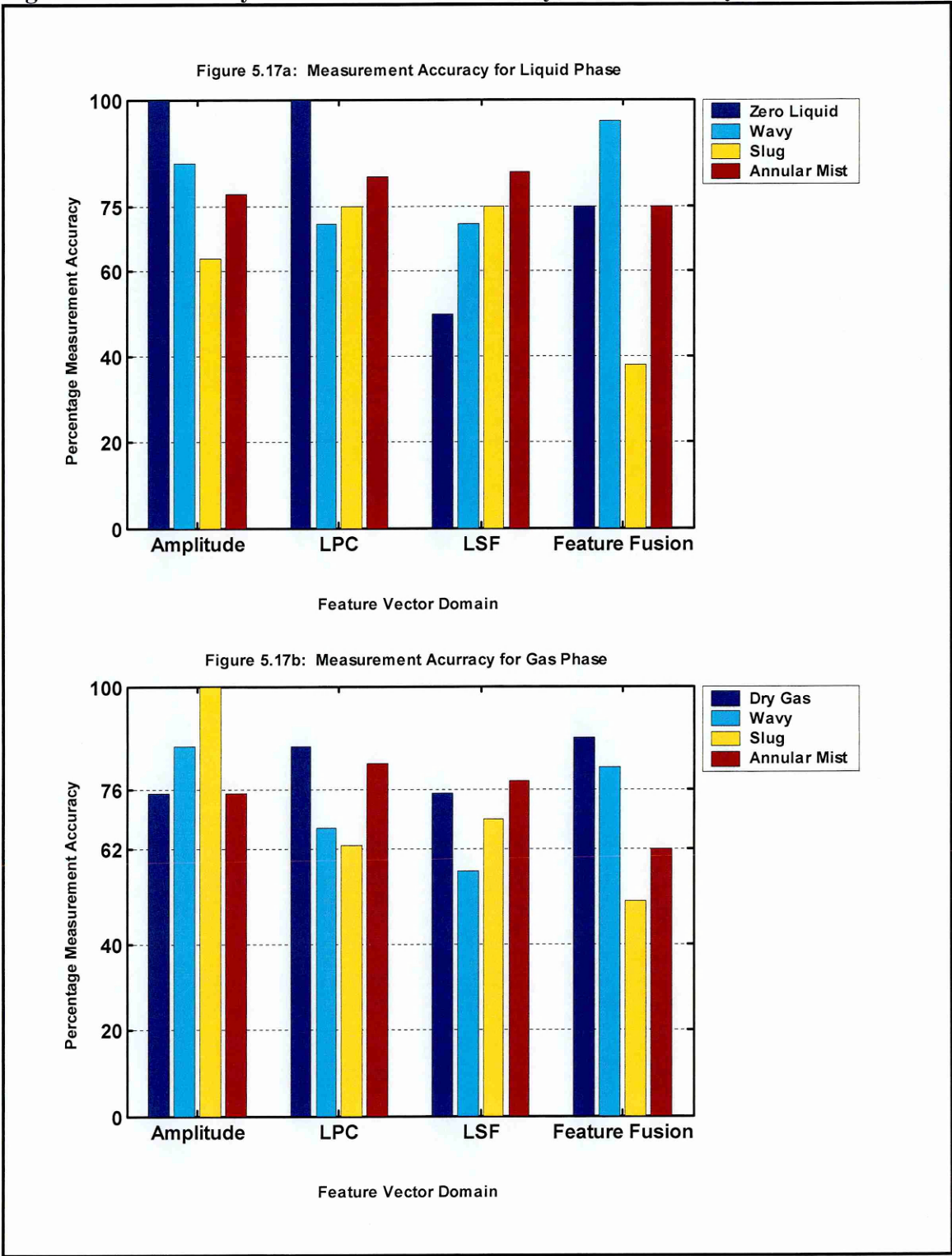


Figure 5.17: Summary of Measurement Accuracy of the Recovery DP



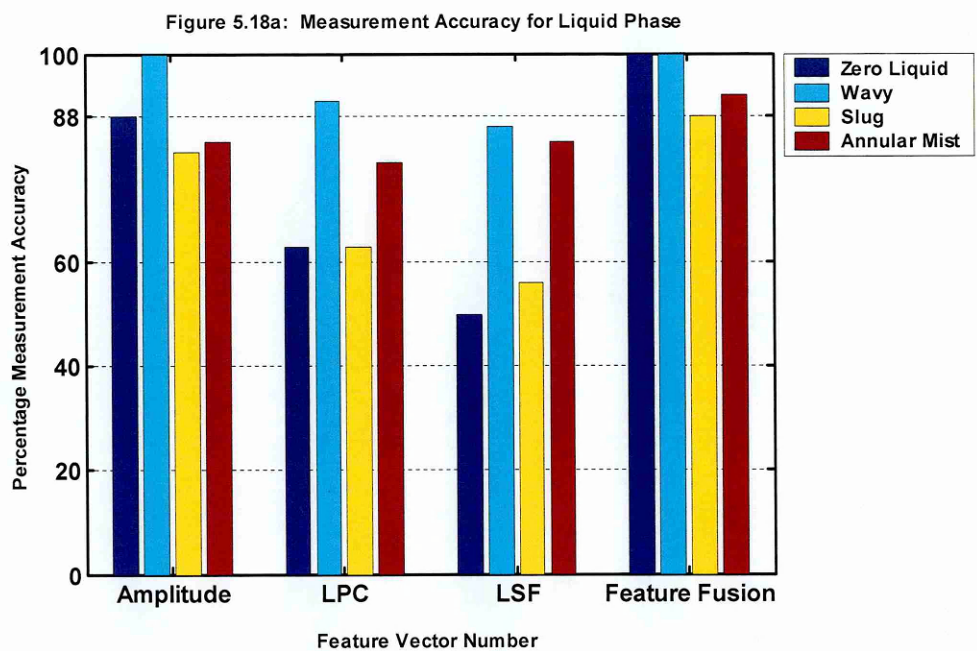
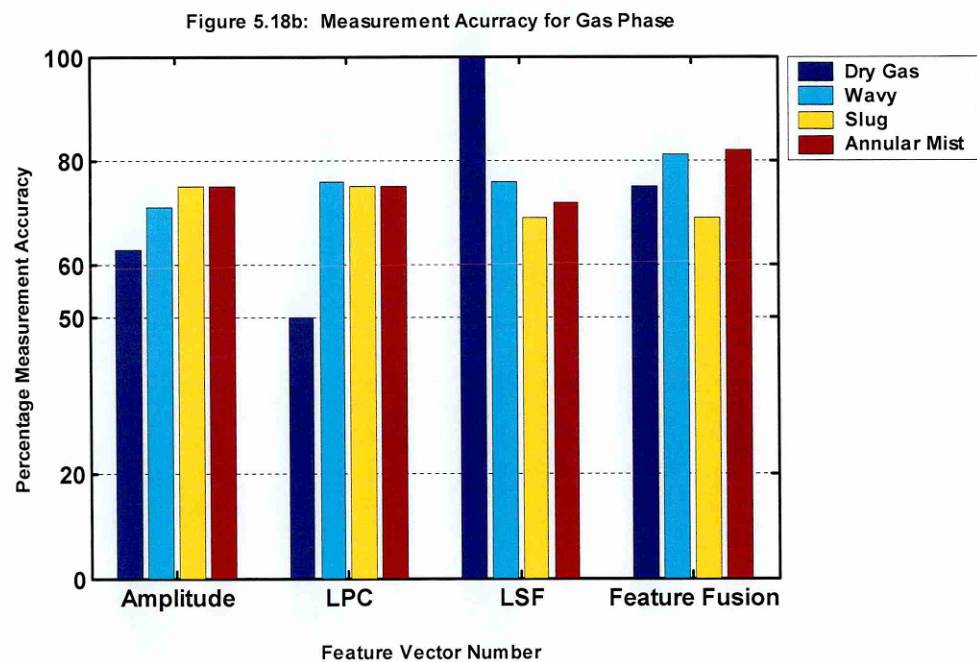
5.4.3 Venturi Absolute Pressure (AP01) Flow Rate Measurement Results

The absolute pressure sensor was also subjected to the same analysis as the throat and recovery length differential pressure sensors of the Venturi meter. The results obtained for both the liquid and gas velocity predictions are given below.

The measurement accuracies achieved by the various feature vectors of the absolute pressure sensor is given in Figures 5.18a and 5.18b. For the liquid phase measurements, the amplitude feature vectors and the feature fusion case do well on detecting the liquid presence by achieving 88 and 100 % of the test points to within ± 5 % error band. These two feature vectors also perform well in all the other flow regimes, with both achieving a measurement accuracy of 100% in the wavy flow regime. On the gas phase, the different feature vectors achieve comparatively similar results with the exception of the linear prediction coefficient feature vectors, which obtained 50 % in the dry gas flow rates. The line spectral frequency feature vectors (LSF) resulted with the best measurement accuracy in the dry gas flow rates with 100 % measurement accuracy.

The absolute pressure sensor consistently achieved better results in the wavy and in the annular mist flow regime. This is caused by the location of the sensor, which is at the bottom of horizontally installed Venturi Meter and the respective flow regimes. Both the wavy and annular mist flow regimes are characterised by a thick liquid layer at the bottom of the pipe, which means that the sensor will be more sensitive to liquid flow rate and less so to the lighter gas phase flowing above it. This type of sensor performance and behaviour is also a confirmation that the sensor is functioning and responding correctly to the flow conditions.

Figure 5.18: Measurement Accuracy of the Absolute Pressure Sensor

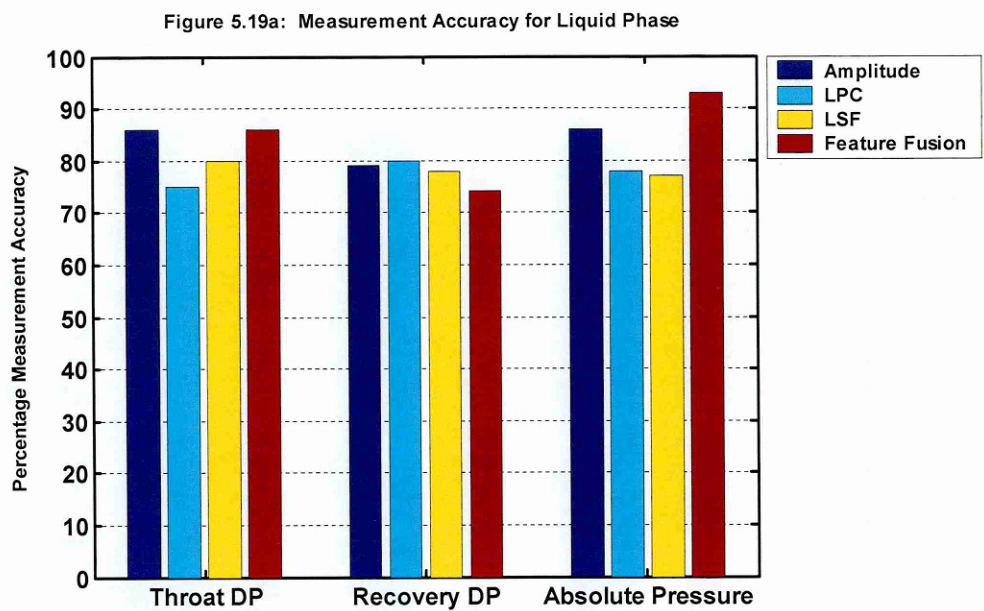
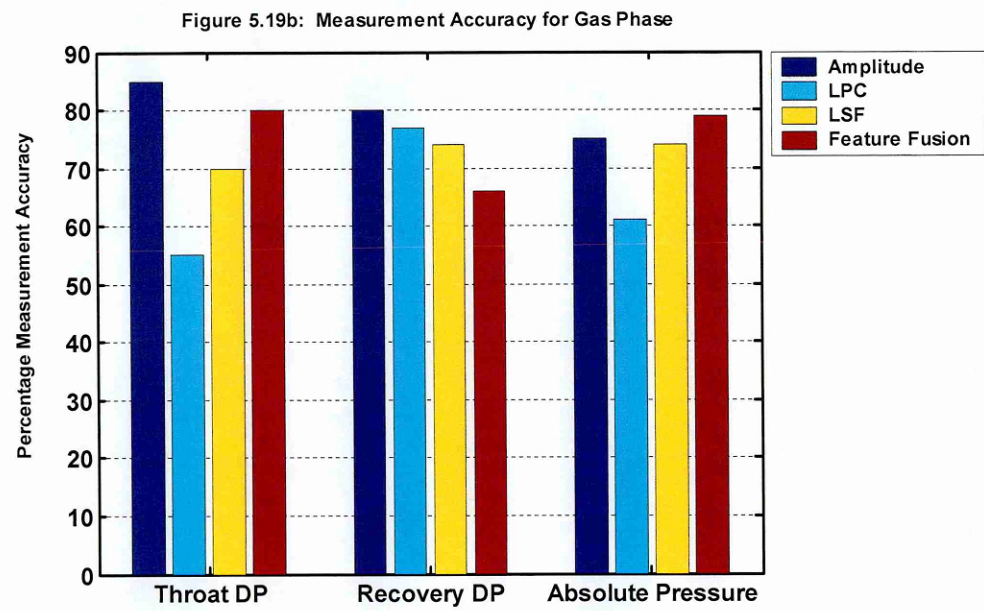


5.4.4 Comparison between DP12, DP13 and AP01

So far the flow rate measurement performance of each sensor has been presented. There were varying levels of measurement accuracy achieved by the different information domains of the three pressure sensors. To sum up the forgoing results and analysis, consider Figures 5.19a and 5.19b below. The accuracies provided here are the overall measurement accuracies over the flow domain of interest. As shown in Figure 5.19a, the fused feature vectors of the absolute and the throat differential pressures achieve the best measurement accuracy on the prediction of the liquid flow rate. The amplitude feature vectors of the absolute and throat differential pressure sensors closely follow this lead. This is not surprising as both sensors are located on the bottom of the horizontally mounted Venturi meter. The linear prediction coefficients and the line spectral frequencies achieve comparatively similar results in all the three pressure sensors.

On the gas flow rate measurement results (Figure 5.19b), the amplitude features of the throat differential pressure and the Venturi recovery length pressure sensors accomplish the highest measurement accuracy. From the above results it may be concluded that when comparing the three pressure sensors the throat differential pressure and the absolute pressure sensors have consistently resulted in the highest measurement accuracy and that the amplitude feature vectors achieved the best flow rate classification accuracy. Furthermore when feature fusion was employed within each sensor, only the absolute pressure and the throat differential pressure sensors have resulted with an accuracy gain over some of the individual feature vectors. In other words, when feature fusion was used with the Venturi length differential pressure sensor (DP13), the measurement accuracy obtained was lower than each of the individual feature vectors on its own.

Figure 5.19: Comparison between Different Sensor Performances



The above results indicated that in addition to feature fusion, the measurement accuracy might be improved even further by cross sensor data fusion. The results obtained with cross-sensor data fusion will now be presented below.

5.4.5: Flow Rate Measurement using Cross-Sensor Data Fusion

In the light of the foregoing results and discussions, it is clear that the neural network model prediction ability is heavily dependent on the type of feature vector combinations used as well as sensor type. The above results indicated that if the flow information from different sensors is fused together, then there is a potential of achieving greater measurement accuracies in all the flow regimes studied. This potential is primarily due to the fact that each sensor has a defined operating range, outside, which its accuracy reduces and by combining and fusing stochastic features from different sensors, the overall accuracy for flow rate measurement may be extended.

There are many different ways that sensor data fusion can be achieved and many of these were tested during initial test screens in the current study. These included extracting the same feature (e.g. AV_{throat} , $AV_{recovery}$ and $AV_{absolute}$, etc) from each sensor and fusing them together to form feature vectors to be input to the neural network model. Other trials included extracting different features (e.g. AV_{throat} , $A1_{recovery}$ and $LSF1_{absolute}$, etc) and constructing a set of input feature vectors. Feature fusion of each feature domain was also tested, whereby the amplitude features from throat DP, recovery DP and absolute pressure sensor were combined to form a total of 18 feature vectors. Similar procedure was also conducted for the linear prediction coefficient (LPC) and the line spectral frequencies (LSF).

After comparing the network performance when using the above different feature combinations, it was found that the best network generalisation was achieved when feature fusion of the same feature domain was used. That is to say, fuse the amplitude features of the throat DP, recovery DP and absolute pressure sensor, and similarly the LPC and LSF respectively. This technique retains the same feature domain, but expands

the feature size by combining different sensor data. Table 5.2 below shows the resultant features chosen in this study for the study of cross-sensor data fusion.

Table 5.2: Cross-Sensor Data Fusion Feature Vectors

	1	2	3	4
Feature Domain	DP12-DP13 Feature Size	DP12-AP01 Feature Size	DP13-AP01 Feature Size	DP12-DP13-AP01 Feature Size
Amplitude	12×122	12×122	12×122	18×122
LPC	12×122	12×122	12×122	18×122
LSF	10×122	10×122	10×122	15×122

As shown in Table 5.2, there were 12 different scenarios to be considered for the study of sensor data fusion. Summaries of the flow rate classification result are given in Table 5.3 below. The results in Table 5.3 are in terms of percentage accuracy classified by the neural network model to within ±5 % measurement error. The highest measurement results were obtained by the amplitude cross-sensor data fusion of the two differential pressure sensors (DP12 and DP13) and the absolute pressure sensor (AP01), followed by the amplitude cross-data sensor data fusion of DP12 and AP01. The linear prediction coefficients have resulted with the lowest measurement gain from sensor data fusion.

Table 5.3: Cross-Sensor Data Fusion Measurement Accuracy

Sensors	DP12-DP13		DP12-AP01		DP13-AP01		DP12-DP13-AP01	
Relative Measurement Error	$0 \leq e \leq 5$		$0 \leq e \leq 5$		$0 \leq e \leq 5$		$0 \leq e \leq 5$	
Amplitude Features	V_{sl}	V_{sg}	V_{sl}	V_{sg}	V_{sl}	V_{sg}	V_{sl}	V_{sg}
	96	90	98	96	91	84	100	100
LPC	69	58	69	55	54	45	79	68
LSF	73	69	74	70	68	60	85	76

The above results show that sensor data fusion is only beneficial when specific types of features and certain types of sensors are used. In the current work, sensor data fusion has indicated significant flow rate measurement improvement only with amplitude feature vectors. These results together with the previous results of feature fusion with the same sensor confirm that the best combinations of sensors to be used for flow rate measurement are the Venturi throat differential pressure sensor and the absolute pressure sensor, and that the most important feature vectors are those of the amplitude domain. In fact from Table 5.3 it is evident that the use of the amplitude features of DP12 and AP01 will suffice to obtain 98 % and 96 % of the liquid and gas test data to within ± 5 % without the need to use DP13.

Figures 5.20a and 5.20b shows the error distribution by the amplitude feature vectors of the combined sensors of DP12-DP13-AP01 on the liquid and gas velocity predictions. As it is evident from these figures 100 % of both phases are predicted to within ± 5 % error band in all the flow regimes. Figures 5.21a to 5.21b also show the measurement error as a function of GVF when only the DP12 and AP01 are utilised.

The predicted gas volume fraction (GVF) in the dry gas data set is between 0.999 and 1. This demonstrates the concept that, pattern recognition as used with the current sensors and Venturi set up could be used to detect the presence and development of liquids in dry gas or condensate wells/pipelines and then as liquid production increases and flow regimes change measure both the gas and liquid flow rates simultaneously. This is a very useful finding, as it means that the pattern recognition system can determine the flow condition in the pipeline so that when, say the liquid volume fraction is below a threshold value (very close to zero, $\sim 0.01\%$), the standard dry gas Venturi equation could be used, while above this threshold, the pattern recognition system would be used for the simultaneous gas and liquid flow rate measurements. This would allow a 'hybrid' system incorporating a dry gas calibrated Venturi meter and smart pattern recognition system to be invoked in multiphase flow conditions. Figures 5.22 and 5.23 using the cross-sensor data fusion of the amplitude feature vectors of DP12-DP13-AP01 and DP12-AP01 respectively illustrate the pattern recognition performance as a liquid detection system.

On the x-axis of these Figures are the actual test data points. It can be seen that the predicted liquid volume fraction (LVF) in the first eight data points is zero, confirming the presence of dry gas conditions (Figures 5.22a and 5.23a). Conversely the system is able to predict the gas volume fraction (GVF) as 1 in the first eight data points (Figures 5.22b and 5.23b). Beyond the dry gas conditions the PR system is able to predict the LVF and GVF simultaneously. In practical applications the GVF and LVF can be plotted against time to monitor their development online.

Figure 5.20: Error Distribution from Amplitude Sensor Data Fusion for DP12-DP13-AP01

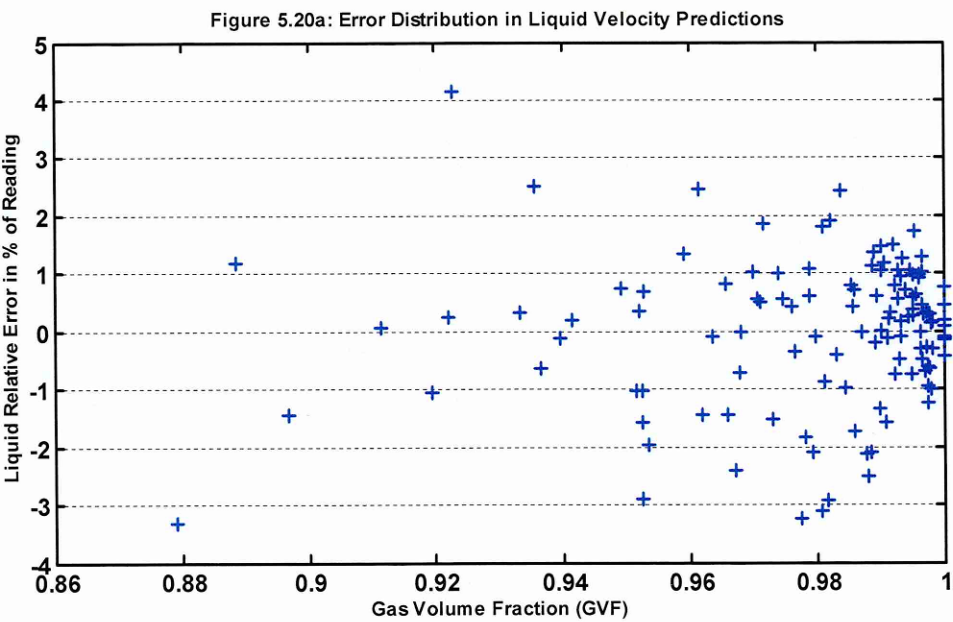
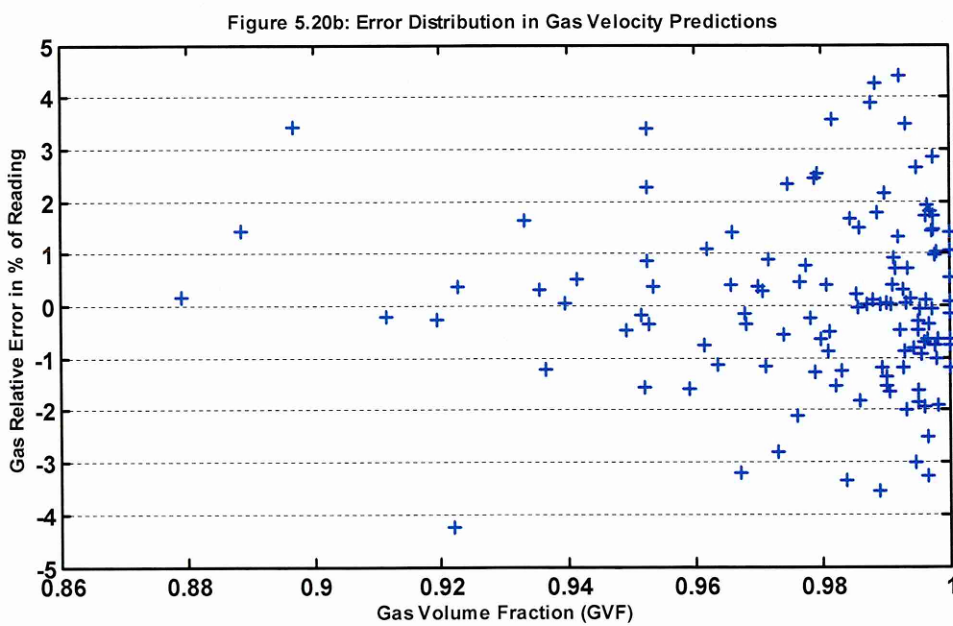


Figure 5.21: Error Distribution from Amplitude Cross-Sensor Data Fusion for DP12-AP01

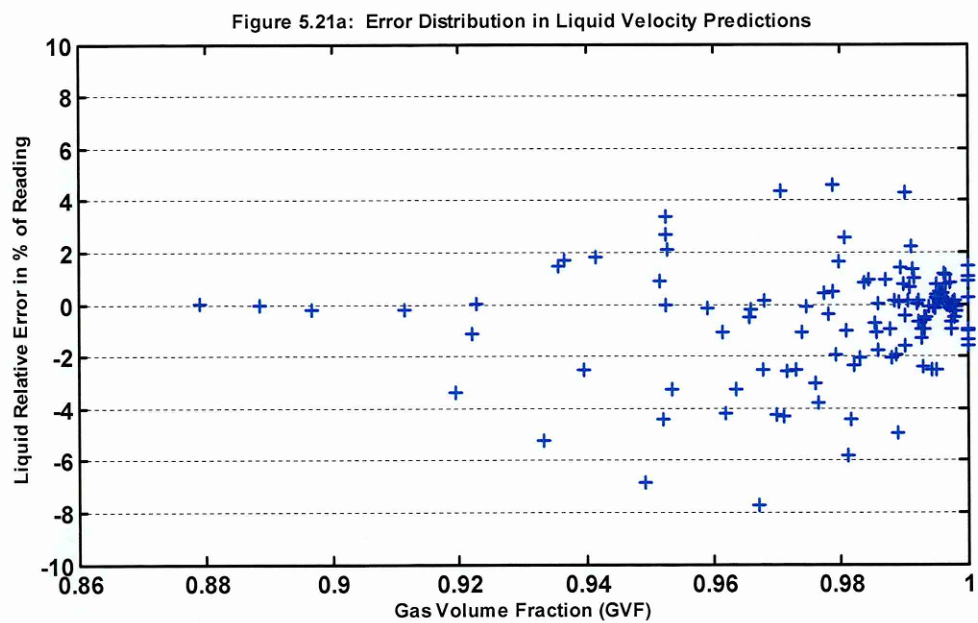
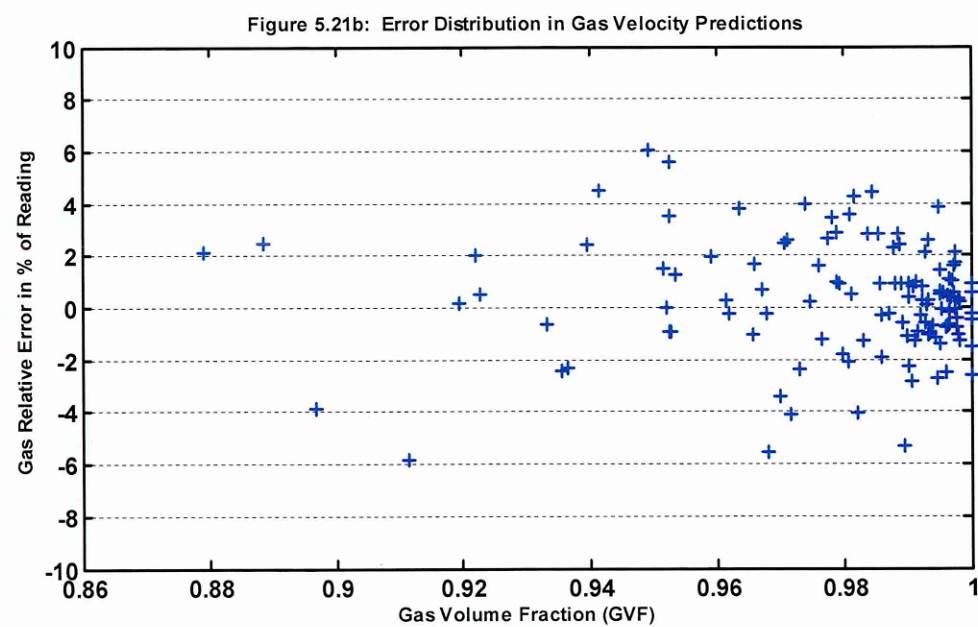


Figure 5.22: Liquid and Gas Volume Fraction Measurement using DP12-DP13-AP01

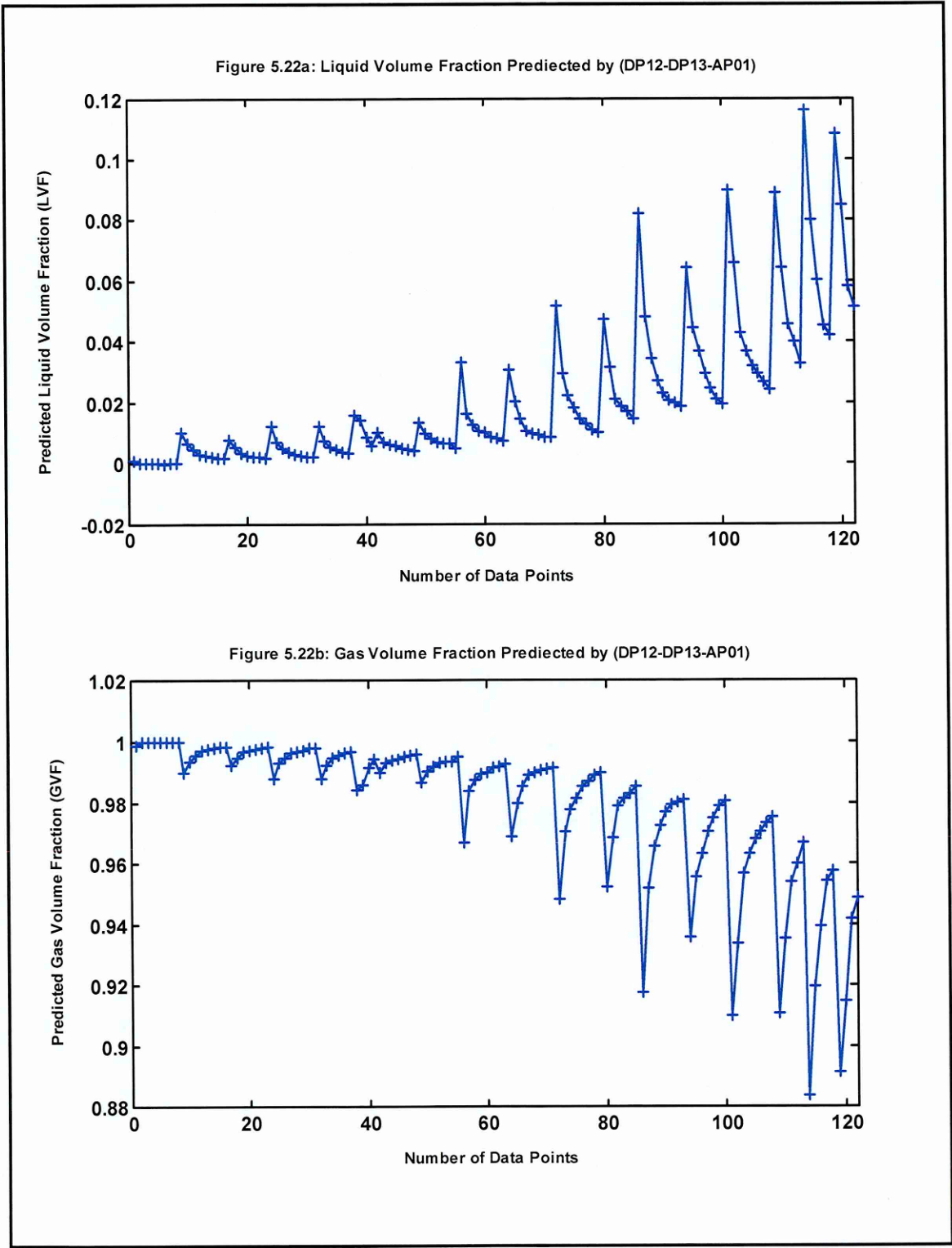
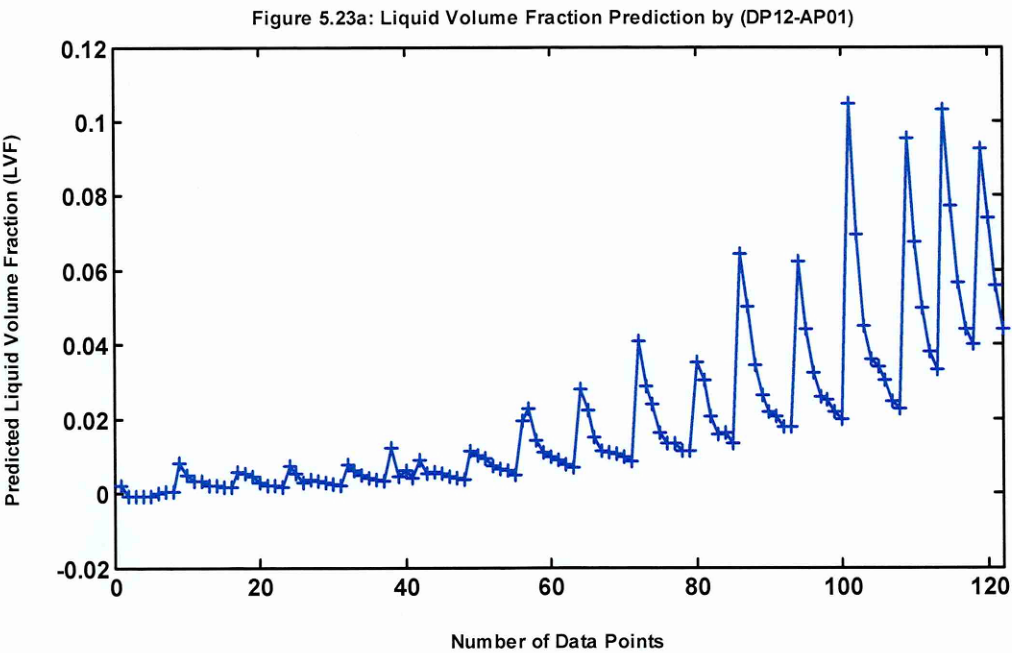
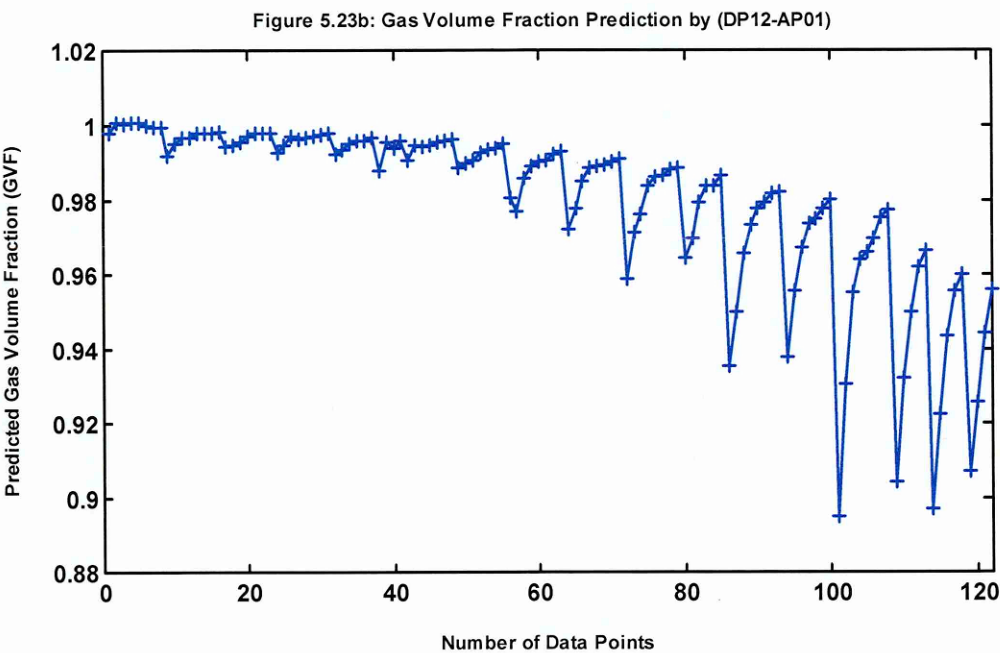


Figure 5.23: Liquid and Gas Volume Fraction Measurement using DP12-AP01



The results presented thus far showed that the pattern recognition system developed in this work is capable of measuring both the gas and liquid flow rates in wet gas flow conditions. Furthermore it was established that the same pattern recognition metering system could be used across the whole domain of interest. This is an extremely important finding as most of the commercially available wet gas meters are only designed for wet gas metering (i.e. annular/mist flow regime) and cannot be relied upon if slugging or other flow regimes present themselves to the metering system.

The proposed pattern recognition system however, relies on the provision of wide-ranging calibration database, which covers as much as possible of the operating envelope and the surrounding flow regimes. As chapter 4 clearly illustrated all the different feature vectors used in this study are sensitive to flow regime, as they showed that their trend and response change as they pass from one flow regime to another. Another key operating parameter is the system operating pressure, which could also affect the developed pattern recognition system. The effect of flow regime change and pipeline operating pressure on the developed pattern recognition system will now be presented below.

5.4.6 Flow Regime Effects

The approach taken to study the effect of flow regime change on the developed pattern recognition technique is to calibrate the system with the data in annular mist flow regime and test it with data from wavy, slug, annular mist and dry gas conditions. This is to simulate the situation where the Venturi is calibrated to operate in wet gas flow measurements, and then a change of flow regime occurs. Figure 5.24 below shows the test matrix selected to study the effect of flow regime, whereby 111 data points are selected for testing and 161 points for training the network. Note some test data are drawn from the annular mist flow regime, so that the system performance within the design envelope can also be checked. Different feature vectors were initially tested, however the best performances were achieved by the cross-sensor data fusion of DP12 and AP01 and the three-sensor fusion (i.e. DP12-DP13-AP01) using the amplitude feature vectors. The results presented below are for the case of DP12-DP13-AP01 using

the amplitude features extracted from these three sensors. A two-layer neural network model having the structure $m-10-2$ was used, where m is the input feature vectors in 18×111 and with 10 neurons in the hidden layer and two neurons in the output layer.

Figure 5.24: Test Matrix for the Study of Flow Regime Effects

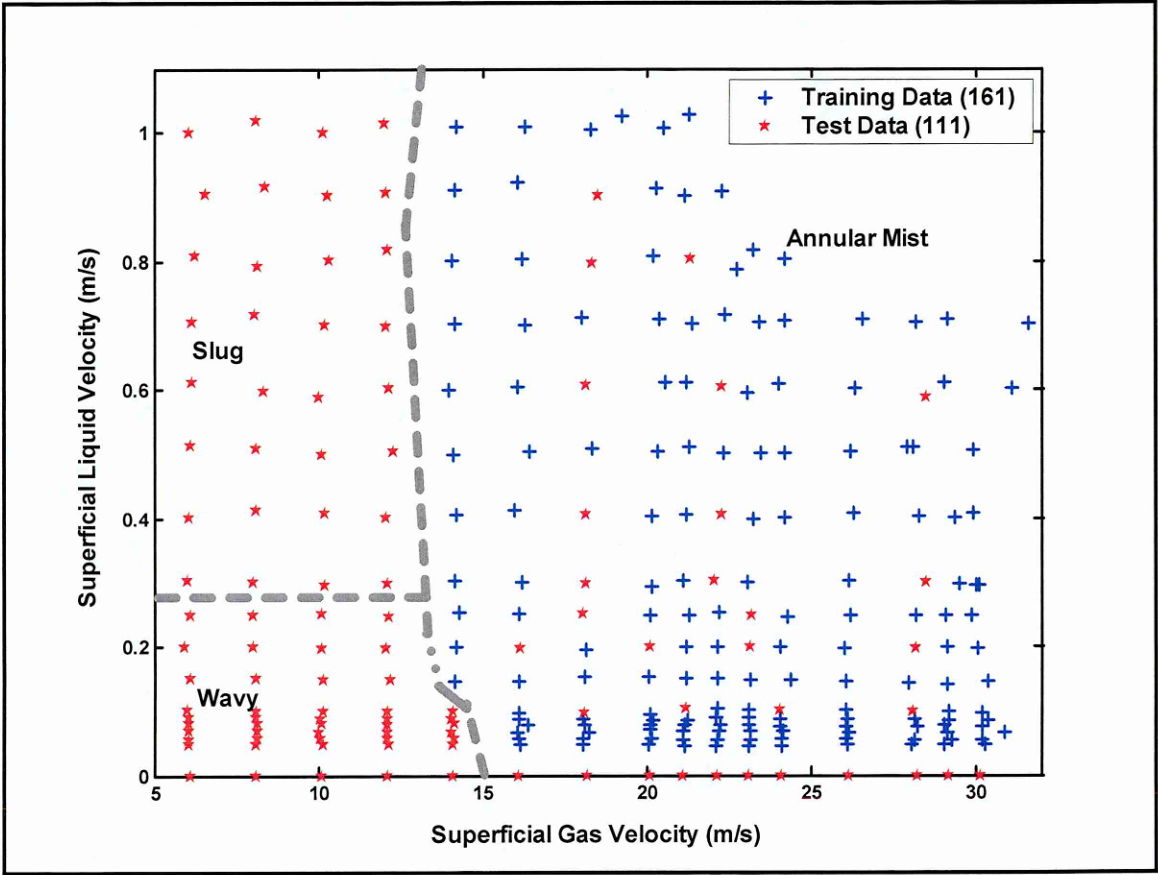


Figure 5.25a shows the prediction results achieved for the liquid flow rate in different flow regimes, where the effect of flow regime change is clearly evident. As expected the system performs well in the annular mist flow regime, as it is now operating in interpolation mode (with measurement accuracy $\pm 5\%$). The system also appears to perform quite satisfactorily for the liquid detection, and in some parts of the wavy flow regime, which corresponds to liquid loading of less than 0.2 m/s.

As can be seen in Figure 5.25a, the performance of the measurement system drastically deteriorates as the liquid loading is increased. The effect of the liquid loading on the measurement accuracy clearly manifests itself in the slug flow regime, where the liquid velocity is significantly under-predicted.

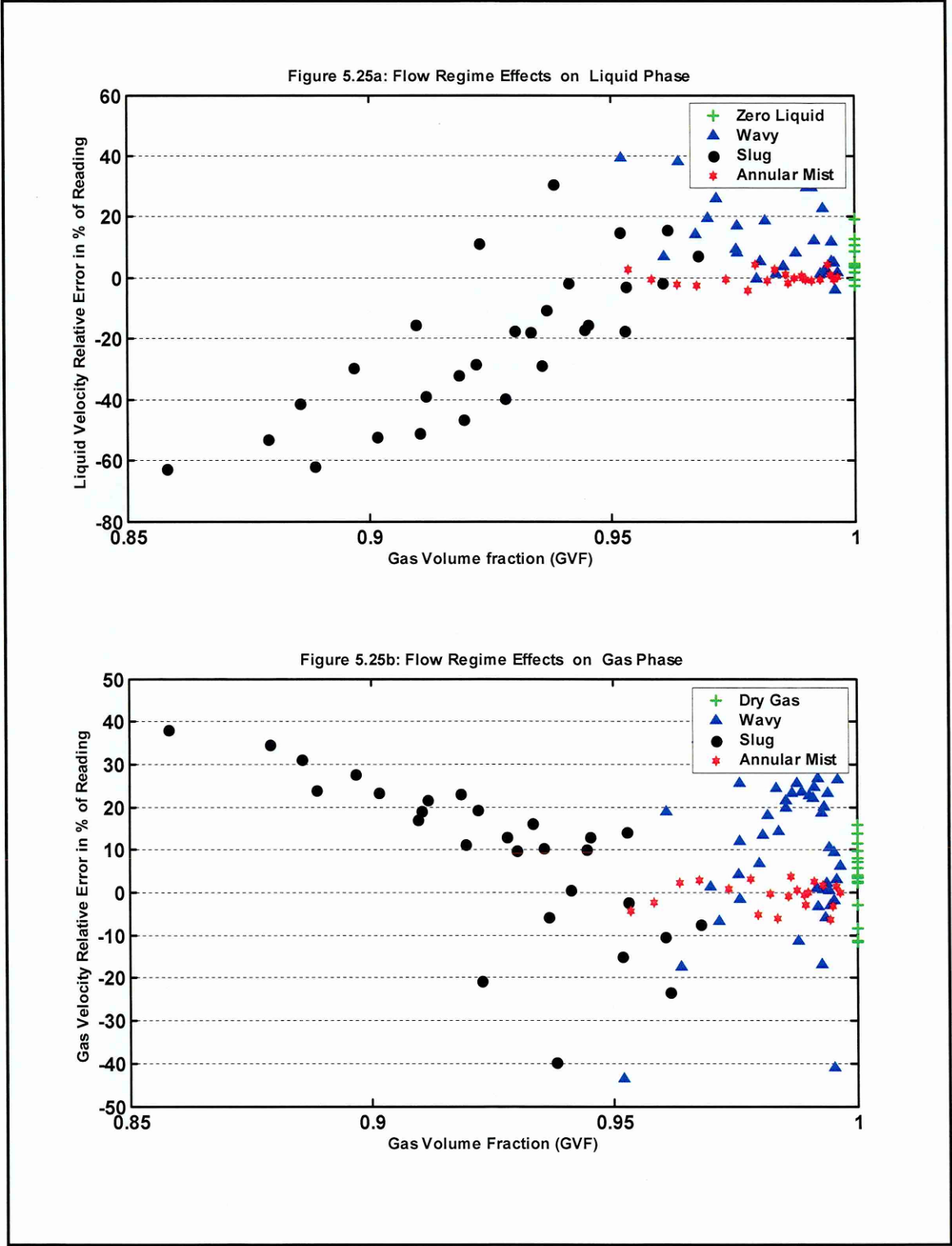
A similar trend can be seen in Figure 5.25b for the gas velocity measurements. The gas velocity prediction for the annular mist flow regime is within the expected range of ± 5 %. The gas velocities in the dry gas conditions as well as in the wavy flow regime are predicted mainly to within ± 10 % measurement error. However, the performance of the measurement system drastically worsens, as the liquid loading is increased, resulting in measurement errors of well beyond ± 10 % in slug flow regimes.

The pattern recognition system performance is fundamentally caused by the change of stochastic features over different flow regimes and their response to changing flow conditions as shown by feature contour plots in chapter 4. As mentioned in the discussion concerning the feature distribution maps in chapter 4, the most distinct feature change is seen in the region between slug flow and annular/mist flow regimes. However, the features response behaviour was relatively similar in the wavy and in the annular mist flow regimes due to the relative similarity between these flow regimes (i.e. both are characterised by a thick liquid layer at the bottom of the pipe and are considered steady-state conditions). Hence this has led to the pattern recognition system performing better in the wavy flow regime than in the slug flow regime.

The above results of the effect of flow regime change reinforce the fact that when neural networks are applied in the field to new data it can be expected to perform well provided the input data is similar to that used during training (as detailed in section 5.21 and 5.22). However, if substantially novel data is presented to the network (as represented by introducing new flow regimes here) then it will be prone to significant errors. This is because the multi layer perceptrons (MLP) networks are discriminators rather than detectors, which mean that they do not generate closed class boundary measures.

The availability of a controlled test rig or validated and wide-ranging field data should allow the collection of extensive data under a sufficiently wide range of conditions (flow regimes) to ensure that the network performs satisfactorily in the field even if unexpected flow condition develop. However, when conditions are known not to remain constant and it is not practically possible to train the pattern recognition system with flow conditions outside the wet gas flow envelope, it would be useful for the system to output along with the classification of input data, a measure of confidence of this decision or to refuse to make a decision if the input data is found to come from a completely new class (e.g. slugging conditions in a wet gas transportation pipeline). A technique involving the use of probability density estimation with MLP neural network output can be used as a measure of novelty. Probability density functions describe the frequency of occurrences of an observation that occur in any point within a domain of interest. Further information of this technique is given in chapter 7, section 7.2 as part of possible extensions of the current work.

Figure 5.25: Measurement Accuracy and Flow Regime Effects



5.4.7 Operating Line Pressure Effects

The pattern recognition system that has been developed in this research study is based mainly on a data collected at an operating pressure of 1 bara (operating pressure is measured by AP01 in Figure 3.3). The effect of change in line operating pressure on the pattern recognition developed will be investigated below.

For the purpose of this study 30 data points have been singled out for comparison purposes. Figure 5.26a shows that the comparison is conducted on distinctly different line pressures, in order to ensure that the effect of line pressure is clearly demonstrated. Figures 5.26b to 5.26d show the flow regime boundaries as visually observed and recorded during the experimental tests. It is immediately evident from these figures that operating pressure change has significantly changed the flow regime boundaries, such that the annular/mist region expands into lower gas velocities. The main reason for the boundary change may be attributed as being due to the increase in gas density as the line pressure is increased (water is incompressible at these pressures), which results in higher pressure drops for the same superficial gas and liquid velocities.

Comparing feature contour maps at different pressures over a common flow domain can show precisely the effect of change in pressure on their trend and responses. Figures 5.27a to 5.27c show the AV feature vector (average pressure drop of the throat DP) at 1, 2 and 3 bara line pressure. The contour lines are calculated by selecting the feature values that are common to all the line pressures studied (i.e. AV=10, 12, 14, 16, 18 and 20 mbar). It can be seen that the feature's contour levels move to lower gas and liquid velocities as the line pressure is increased, resulting in a higher pressure drop for the same intersection points of superficial gas and liquid velocities.

Since the input data to the neural network model are normalised, it is necessary to observe the normalised features trends to operating line pressure. Figures 5.28a to 5.28f show the normalised contour maps of the AV of throat DP (DP12). The observed feature

behaviour suggests that normalisation lessens the effect of line pressure as the location of feature values and contours changes slightly as compared to the un-normalised cases.

In evaluating the network performance with operating line pressure changes, three scenarios were considered. The first two scenarios are to train the network with the data at 1 bar, while testing its generalisation performance with data at 2 and 3 bar respectively (extrapolation mode). The 3rd scenario is to train the network with data gathered at 1 and 3 bar and test the generalisation performance of the network with 2 bar data (interpolation mode).

Figures 5.29a to 5.29f show the relative measurement errors obtained with the above three scenarios as a function of gas volume fraction. It is evident from these plots that the network results are subject to significant errors in scenarios 1 and 2, but with slightly better results in scenario 1 than 2 (Figures 5.29a to 5.29d), due to the magnitude of the pressure change.

It is evident from these results that the shift in flow regime map severely affects the feature behaviour such that for the same inlet conditions (i.e. superficial gas and liquid velocity), the feature value and its distribution does not remain constant, but rather shifts in response to the pressure change. This behaviour in feature response, consequently affects the network performance.

The above results suggest that prior to applying pattern recognition techniques to real world applications in the field the system must be calibrated with data collected under a sufficiently wide range of conditions (e.g. line pressure, flow regimes, fluid properties, etc). In terms of operating line pressure, this would require the provision of training data, which is collected under the system operating pressure, and if possible some data in extreme conditions (Min and Max expected operating pressure). The operating pressure would normally fluctuate and vary by a small amount and the pattern recognition system should be expected to extrapolate well in these conditions. For instance, most of the data discussed in sections 5.4.1 to 5.4.5 of this chapter were collected within 1 bara, however

this became practically impossible to attain under higher liquid loading (slug and mist flow regimes), allowing the operating pressure to fluctuate between 1 to 2 bar under these conditions. Nevertheless the network performed well in these conditions, due to the fact that there was no sudden step change in system operating pressure, but rather a gradual change. The most desirable operating mode therefore for pattern recognition models would be an interpolation mode with extrapolation allowed only in small and gradual changes. However, in cases where the system is expected to experience a sudden and large operating pressure changes, the absolute pressure measurements may be monitored closely, and if this changes significantly from a predefined threshold, the system should be turned into a calibration mode and retrained.

Figure 5.26: Operating Pressure Effect on Flow Regime Boundaries

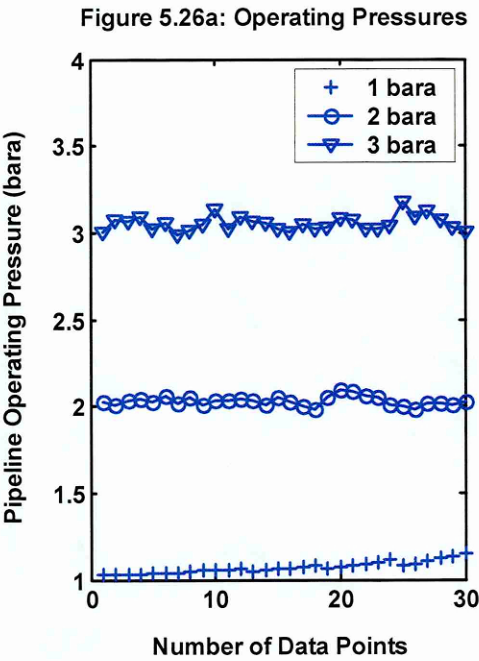
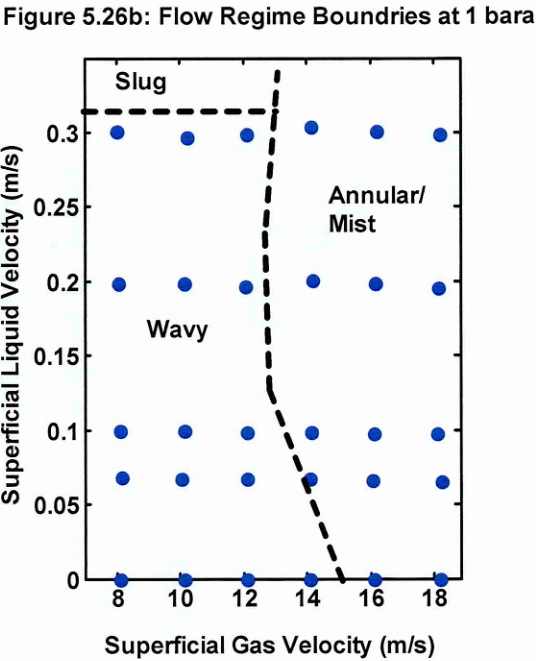
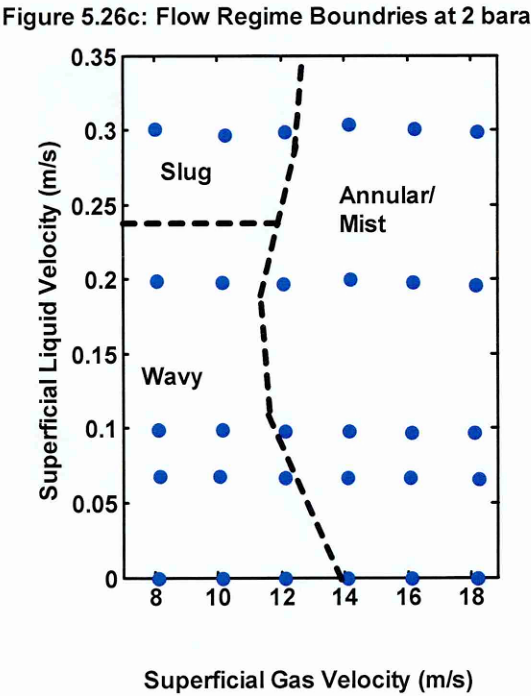
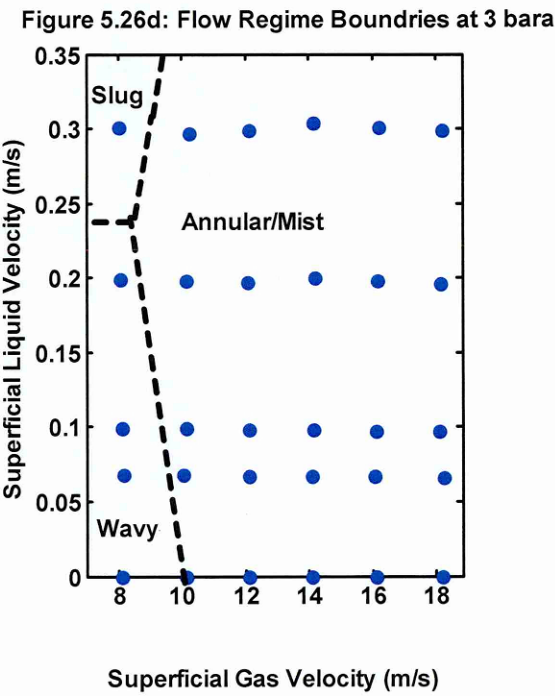


Figure 5.27: Operating Pressure Effect on Original Feature

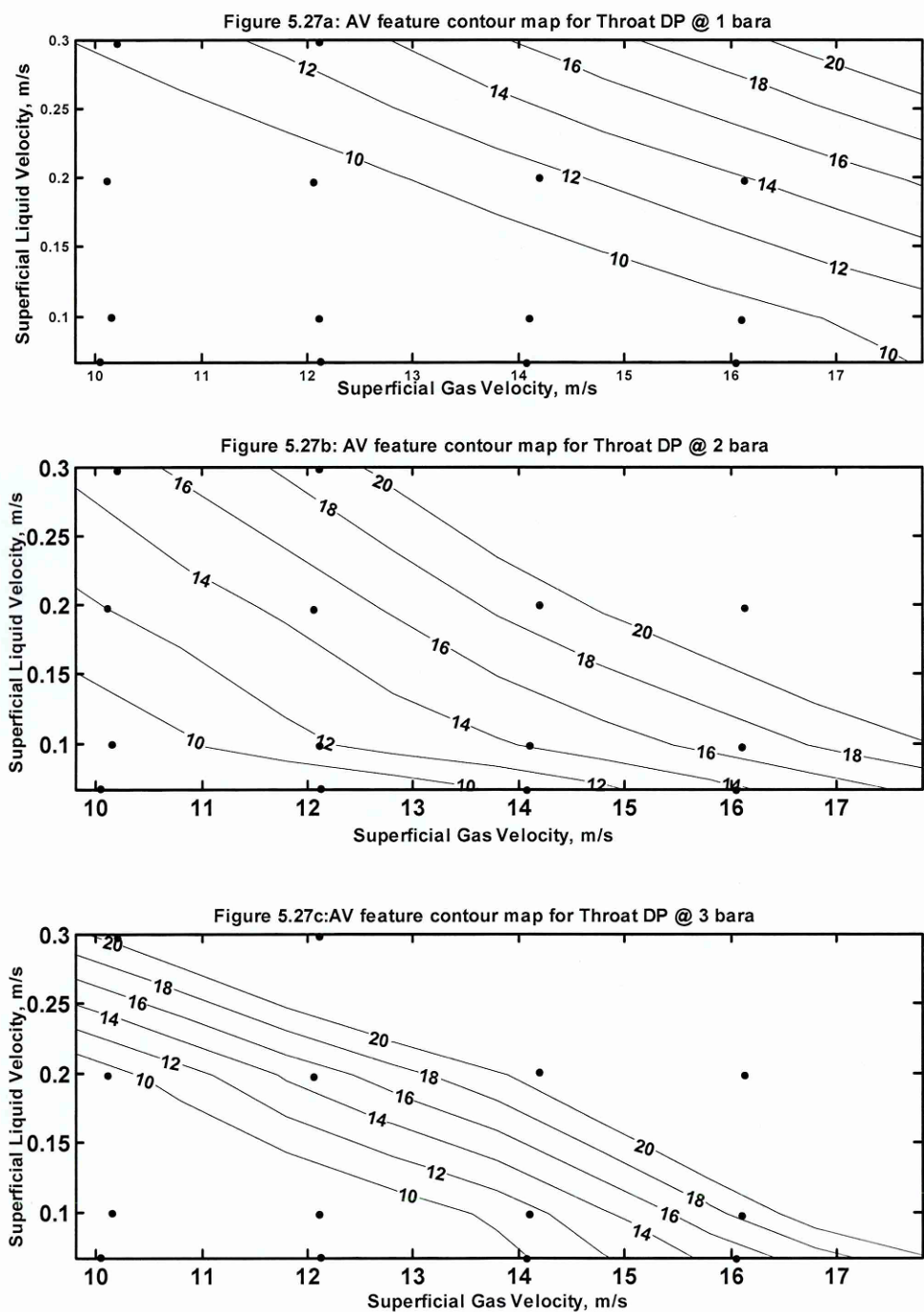


Figure 5.28: Operating Pressure Effect on Normalised Features

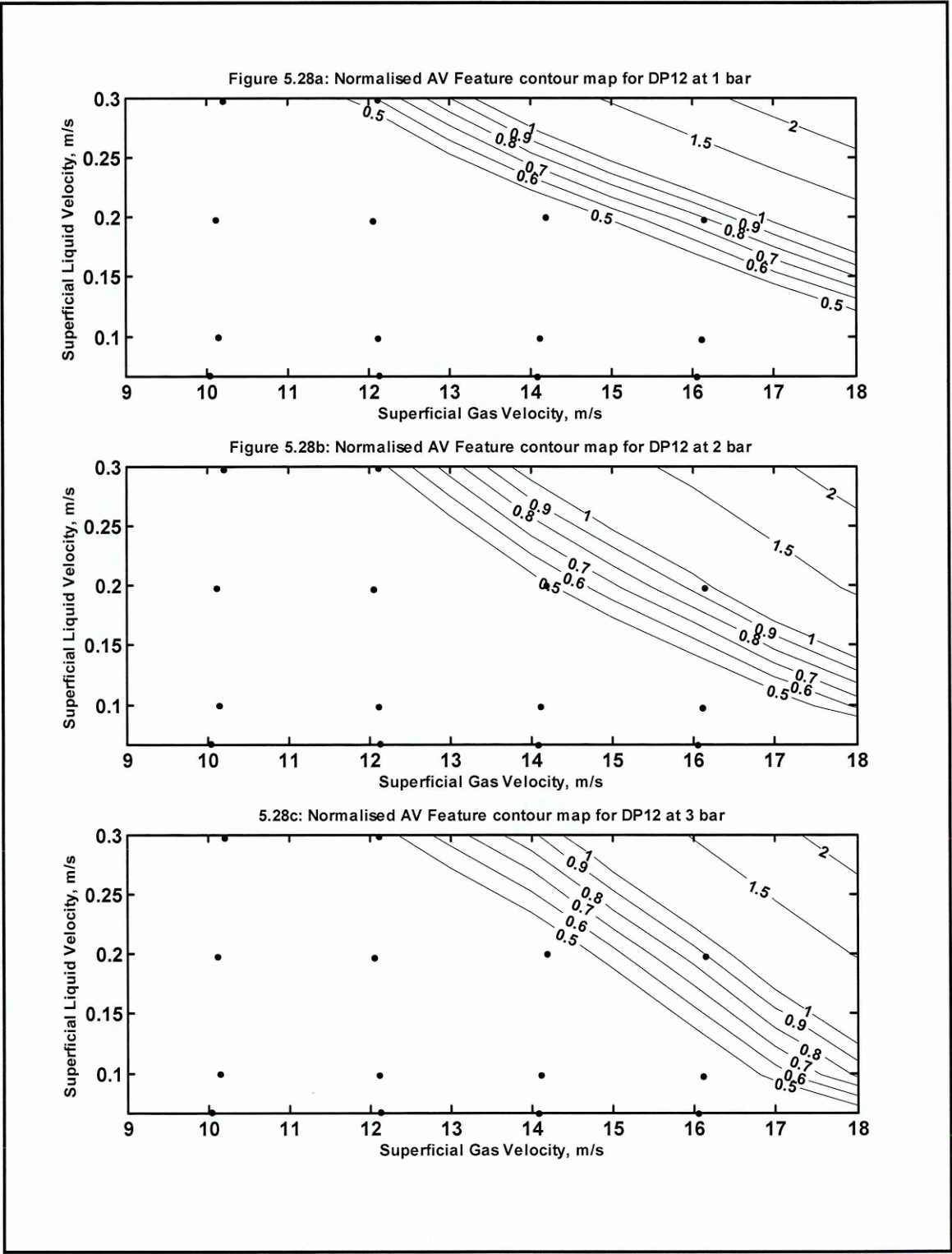
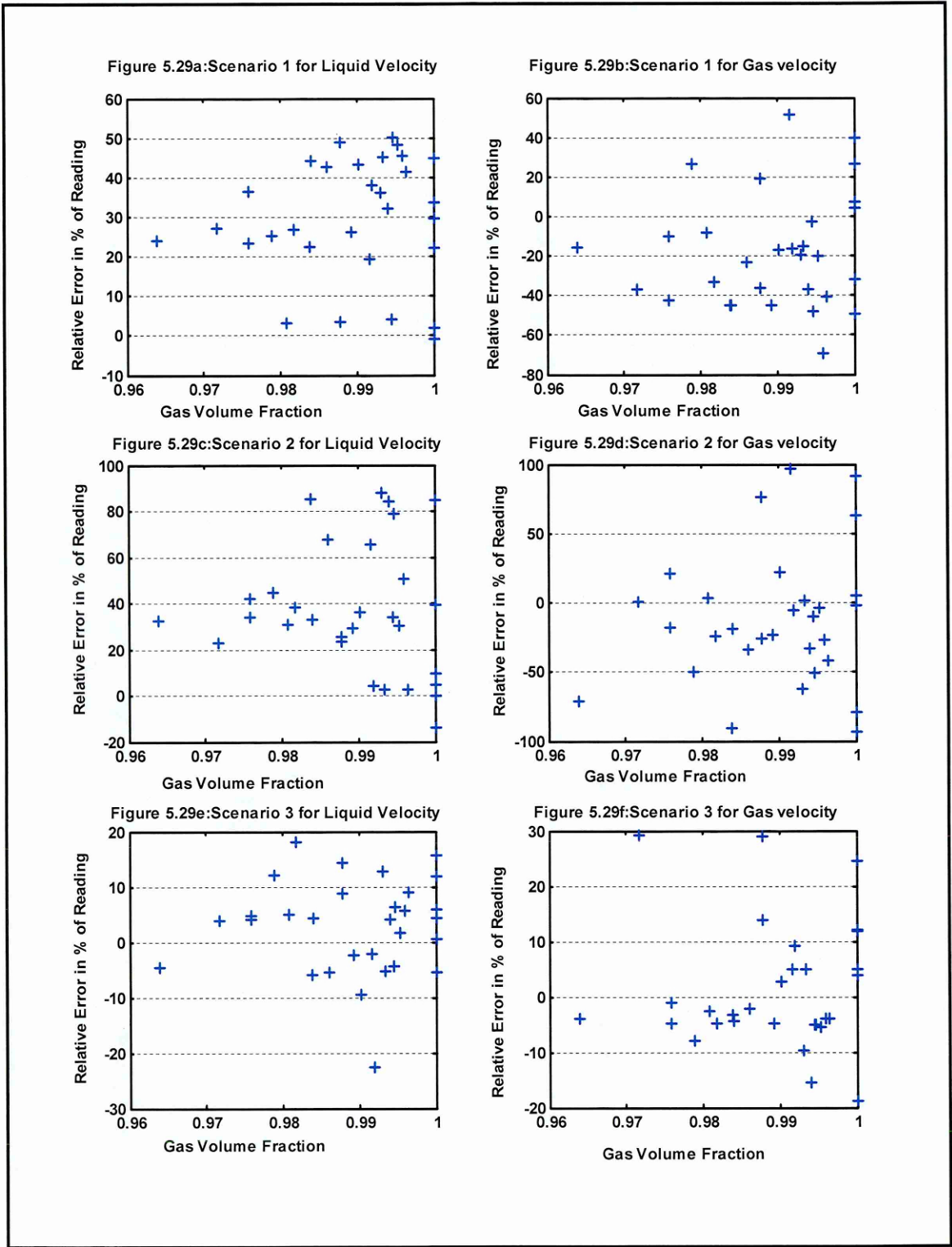


Figure 5.29: Operating pressure effect and Measurement Error Distribution



5.5 Conclusions

This chapter discussed the flow rate measurement results obtained with pattern recognition techniques as illustrated in Figure 5.1. The raw data is measured with three pressure sensors: two axial differential pressure sensors and one absolute pressure sensor (see Figure 3.3 for the Venturi used in this work and sensor locations). The flow rate measurement system is composed of feature vectors extracted from the amplitude, linear prediction coefficients and line spectral frequencies. A Bayesian multi layer (MLP) neural network model is used as the pattern classifier.

The following conclusions can be made from the results presented in this chapter: -

- 1 Stochastic features extracted from differential pressure sensors and absolute pressure sensors of a Venturi meter have an implicit relationship with gas and liquid flow rates (superficial gas and liquid flow rates).
- 2 The Bayesian multi layer perceptron (MLP) neural network classification model used in this study showed it is possible to construct an input-output mapping between the stochastic features and the corresponding individual gas and liquid superficial velocities. The exact form of this mapping is determined from a data set of labelled examples (i.e. training data)
- 3 An added advantage of the Bayesian regularisation MLP neural network is that unlike traditional MLP neural networks, which require a dedicated validation subset to minimise overfitting, the Bayesian technique controls model complexity (overfitting) automatically using only the training data. Furthermore the Bayesian approach improves generalisation and provides a measure of how many network parameters (weights and biases) are being effectively used by the network. It also eliminates the guesswork required in determining the optimum number of hidden neurons and consistently leads to good networks that are not over-trained.

- 4 The flow rate classification results obtained vary considerably depending on which feature combinations and pressure sensors used. The results were also heavily influenced by the flow regime. When only the Venturi throat differential pressure (DP12) was used it was seen that the amplitude features, line spectral frequencies and the feature fusion scenarios have all successfully identified the absence of liquid in dry gas conditions with a relative measurement error of better than $\pm 5\%$. The amplitude features have also identified 100 % of the dry gas flow rates to within $\pm 5\%$.
- 5 In terms of annular/mist flow regime, all the four different feature vectors (amplitude, LPC, LSF and feature fusion) of the throat DP obtained comparatively similar results in liquid superficial velocity measurements with 80 % of the test data measured to within $\pm 5\%$. However in terms of superficial gas velocity measurements, only the amplitude and the feature fusion cases achieved similar results. In the slug flow regime, the amplitude features obtained the highest measurement accuracy for both the gas and liquid superficial velocities. For the wavy flow regime, all the four feature vectors resulted with comparatively similar results (over 80 %) for the liquid phase, whereas in terms of gas superficial velocity, the amplitude features and the feature fusion cases had the highest measurement accuracy with 88 and 100 % respectively.
- 6 It can be concluded that if only the Venturi throat differential pressure (DP12) were to be used for flow rate measurement, then only the extraction of amplitude features should be considered.
- 7 From the Venturi recovery length differential pressure (DP13), the presented results showed that in terms of confirming the absence of any liquid in the pipeline, the amplitude features and the linear prediction coefficients had the highest measurement accuracy, achieving both an accuracy of 100 %. On the

dry gas velocity measurement, it was the feature fusion and the linear prediction cases that had the highest measurement accuracy.

- 8 For the measurement of gas and liquid superficial velocities in the annular/mist flow regime, the four different feature vectors of DP13 achieve respectively similar results ($\sim 80\%$), except the feature fusion scenario, which achieves only about 60% for the gas phase. In the slug flow regime, the linear prediction coefficients and the line spectral frequencies had the highest measurement accuracy for the liquid phase (75%), but on the gas phase the amplitude feature vectors obtained 100% of the test data within the defined error band. The amplitude feature vectors and the feature fusion cases resulted with highest measurement accuracy (85 and 95% respectively) in the wavy flow regime when using DP13.
- 9 The flow rate measurement results obtained by the different feature vectors extracted from the DP13 sensor showed that the amplitude features and the linear prediction coefficients achieved the highest measurement accuracy across the whole flow domain of interest. Hence either of these two feature vectors may be recommended to be used for the simultaneous measurement of gas and liquid flow rates.
- 10 The results obtained from the absolute pressure sensor (AP01) showed that in terms of the detection of zero liquid presence, the feature fusion and amplitude feature vectors had the highest measurement accuracy with 100% and 88% respectively. The line spectral frequency features obtained the best dry gas measurement results with 100% of the test data predicted to within the defined error band.
- 11 In the annular/mist flow rates, the feature fusion case had achieved the best measurement accuracy for both the liquid and gas flow rate measurements (92% and 83% respectively), followed by the amplitude feature vectors. The

feature fusion scenario also had the highest measurement accuracy in the slug flow regime for gas and liquid superficial velocity measurements. The amplitude features and the feature fusion cases had the best measurement results for the liquid phase in the wavy flow regime, each achieving 100 % of test data to within ± 5 %. The feature fusion scenario obtained the best measurement results in the gas phase, with 80 % relative measurement accuracy.

- 12 The optimum feature vectors in terms of the liquid phase for the absolute pressure sensor are the amplitude feature vectors and the feature fusion scenarios. On the gas phase all the feature vectors achieve comparatively closer results with the exception of the linear prediction coefficients with less than 50 % measurement accuracy.
- 13 It may be concluded that when comparing the overall measurement performance of the three sensors and the four different feature vectors that the throat differential pressure (DP12) and the absolute pressure sensor (AP01) achieve the best measurement results for the liquid phase, with the best features vectors being the feature fusion and the amplitude feature vectors. Whereas in terms of the gas phase the results are quite close, with DP13 achieving slightly overall better consistency than the other two sensors.
- 14 The linear prediction coefficients (LPC) and their derivatives, the line spectral frequencies (LSF) are most commonly used for speech coding. In these applications the line spectral frequencies are believed to have a better quantisation and interpolation properties and lead to better system approximation and classification accuracy when used as inputs to a voice recognition system model. As a direct analogy to their application in speech coding and automatic voice recognition, the line spectral frequencies have been shown in this work to lead consistently to better classification accuracy

of the individual gas and liquid flow rates in different flow regimes than the linear prediction coefficients.

- 15 In terms of cross sensor data fusion, the pattern recognition classification accuracy depends on the type of sensors combined and which type of features are fused together.
- 16 When the discriminatory ability of different feature vectors were compared, the cross-sensor feature fusion of the amplitude feature vectors performed markedly better than the linear prediction coefficients and the line spectral frequencies.
- 17 The best measurement accuracy was achieved by fusing the amplitude feature vectors of the three pressure sensors (DP12, DP13 and AP01) followed by the amplitude feature fusion between DP12 and AP01.
- 18 From the cross-sensor data fusion analysis, it may be deduced that for the simultaneous measurements of gas and liquid flow rates, the standard Venturi meter, with no extra sensor installations will suffice. In other words, the absolute pressure sensor and the throat differential pressure sensor, which are normally supplied with classical Venturi meters for single-phase flow measurements will be sufficient for the measurement of both gas and liquid flow rates, without prior knowledge of either phase.
- 19 To simulate a 'liquid break-through' in a dry gas flow pipeline, the pattern recognition system was calibrated with zero superficial liquid velocities. The system was able to measure a liquid volume fraction of less than 0.01% in dry gas conditions. In an operation environment this could be used as a diagnostic test and would confirm the existence of dry gas conditions. In this case both the standard Venturi meter and pattern recognition system can be used to

measure the dry gas flow rates. However as liquid loading increases the system would switch over to the pattern recognition model for the simultaneous measurement of both gas and liquid flow rates.

- 20 The flow rate measurement results by different feature vectors showed that the metering system developed in this study is affected by the changes in flow regimes. However, at the same time, the results showed that if sufficient calibration data is provided in the neighbouring flow regimes to the wet gas flow region then the system could be made independent of flow regime. In other words, the same pattern recognition model could be used in all the different flow regimes, provided the system was calibrated for this purpose at the design stage.
- 21 The results from the study of flow regime effects showed that when the pattern recognition metering system developed here is subjected to a flow regime that was not part of the calibration data, then the system showed significant measurement errors. Most noticeably was the effect of the slug flow regime. If substantially novel data is presented to the network (as represented by introducing new flow regimes here) then it will be prone to significant errors. The availability of a controlled test rig or a validated and wide-ranging field data should allow the collection of extensive data under a sufficiently wide range of conditions (flow regimes) to ensure that the network performs satisfactorily in the field in case unexpected flow condition develop. However, in situations, where the system is expected to experience a sudden change of operating conditions, which is outside the calibration database, a novelty detection may be considered, which should decide when a feature set does not represent any known classes (i.e. gas and liquid flow rates). A possible technique of incorporating a novelty detection algorithm into the PR measurement system is given in chapter 7 as part of possible extensions of the current research work.

22 The analysis of the operating line pressure effects showed when the system was allowed to operate in extrapolation mode, whereby it was trained with input data from 1 bar and tested with data from three bar, the network classification accuracy was very poor. However when the system was operated in interpolation mode by training the system with data from 1 bar and 3 bar, while testing it with data from 2 bar, the network classification accuracy was significantly improved. The absolute pressure can be used as part of a novelty detection system to monitor the system operating pressure, and if this is significantly outside the system calibration database, a decision should be made whether to continue the measurement or retrain the pattern recognition system with the new developing conditions.

To further evaluate the accuracy of the pattern recognition system developed in this work, the results were also compared against existing wet gas (two-phase) flow correlations. This was done considering only the annular/mist flow regime and using only the amplitude feature vectors extracted from the throat differential pressure (DP12) and absolute pressure sensor (AP01). This is discussed in the following chapter.

CHAPTER 6

**EVALUATING PATTERN RECOGNITION RESULTS AGAINST
WET GAS FLOW CORRELATIONS**

Many investigators (see chapter two for review) have proposed expressions for calculating the gas flow rate of a two-phase gas/liquid mixture mostly for orifice and some for Venturi meters. A common underlying assumption of all of these correlations is that the liquid and gas densities as well as gas mass fraction (quality) should be known or measured priori.

Among the two-phase flow empirical correlations published in the open literature six are considered applicable to wet gas flow measurement. These correlations are discussed in detail in chapter 2 and are summarised in Table 6.1 below.

Table 6.1: Empirical Correlations Applicable to Wet Gas Flow Measurements

No.	Author(s) of the correlation	Meter Type	Year of Publication
1	Murdock, J. W	Orifice	1962
2	Smith, R. V. and Leang, J. T	Orifice, Venturi, Nozzles	1975
3	Chisholm, D	Orifices	1977
4	Lin, Z. H	Orifice	1982
5	De Leeuw, H	Venturi	1997
6	Steven, R	Venturi	2002

In addition to the above correlations, two other cases were tested using the current data. The first of these initial cases was to treat the two-phase flow as single-phase dry gas flow and thereby ignoring the presence of the liquid and its effect on both pressure and density. The standard dry gas Venturi equation was used to determine the apparent and uncorrected gas mass flow rate.

Secondly the homogeneous density model was tested. In this case the measured two-phase pressure drop is used together with the two-phase homogeneous density to give a two-phase mass flow rate value, which is then used with the gas mass fraction to derive a corrected gas mass flow rate.

The above two basic cases act as a benchmark above which any proposed two-phase/multiphase correlation must be expected to perform. In other words, for a flow correlation to be considered valid for multiphase flow measurements, it must achieve better accuracy on flow rate predictions than is possible with the two simple cases mentioned above.

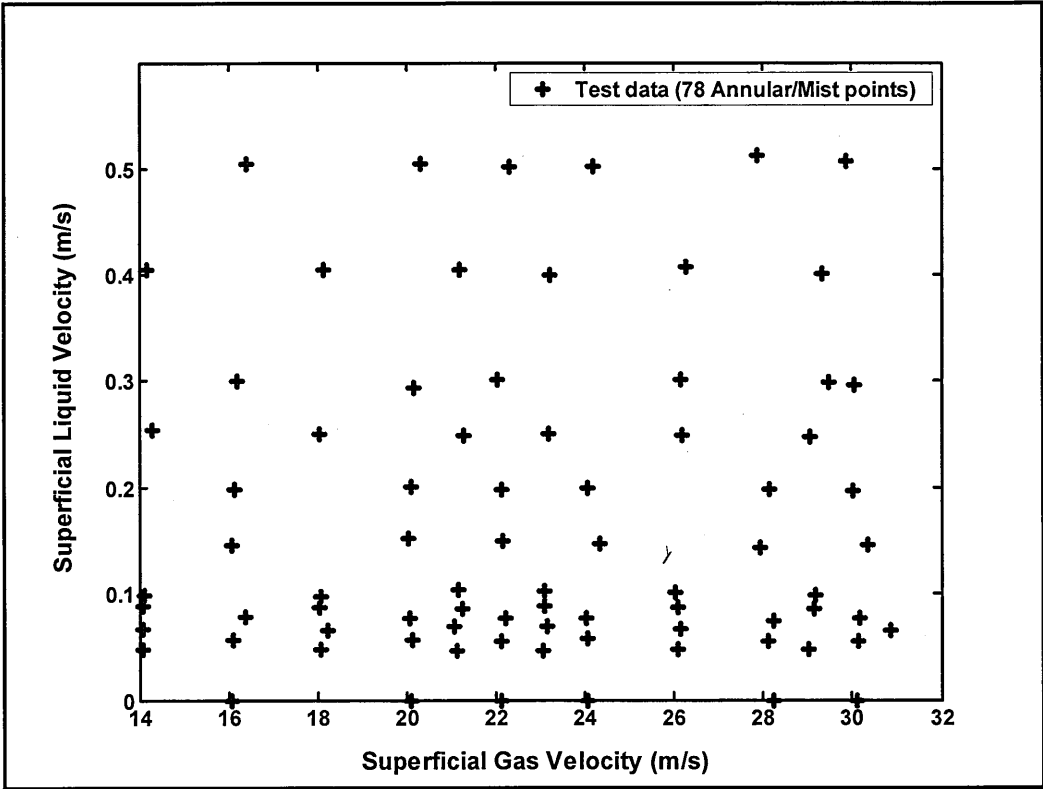
As discussed in chapter 2, the correlations of Murdock (1962), Smith and Leang (1975), Chisholm (1977) and Lin (1982) were developed from orifice plate data for use with general two-phase flow measurements. Furthermore it must be noted that the correlations of de Leeuw (1997) and Steven (2002) are the only published wet gas Venturi meter correlations, however since they conducted their experiments with a different set of conditions (i.e. pressure and fluid properties) than the current data, the main purpose of including them here is to study their generic performance trend.

The pattern recognition model predictions and results were discussed in chapter 5. The amplitude feature vectors of the Venturi throat differential pressure sensor and the absolute pressure sensor (DP12-AP01) were used for simultaneous flow rate measurement of gas and liquid flow rates in conjunction with a 2 layer Bayesian MLP neural network having 10 neurons in the hidden layer and two neurons in the output layer was used (i.e. $12-10-2$). A non-linear, sigmoid transfer function and a linear transfer function were used in the hidden and in the output layers respectively.

6.1 Test Matrix for Comparative Study

Figure 6.1 below shows the test matrix that was used for PR and flow correlation comparison. In order to make the comparison valid for wet gas flow regime, the data points that were covering only annular/mist flow regime were selected. This refers to a two-phase flow with a GVF between 97% to 99.9% as well as dry gas data.

Figure 6.1: Test Matrix for PR and Flow Correlation Comparison



A total of 78 data points were used for the comparison including 6 dry gas data points as shown in figure 6.1.

In order to get a quantitative comparison between pattern recognition and flow correlation-based predictions, a number of criteria were used as follows.

- a) Plot a linear regression fit of the actual (measured) flow rates against the predicted mass flow rates. This will illustrate how close the predicted rates match against the sought after, target flow rates.
- b) Plot the gas mass flow rate relative error as a percentage of reading and as a function of gas volume fraction (GVF), using equation 2.24. This will provide an estimate of the measurement error distribution over the flow domain of interest.

Compare the Root Mean Square Fractional Deviation (d), as calculated by equation 2.43. This gives an estimate of the standard deviation and thereby the spread of measurement errors.

It is to be noted that the dry gas Venturi equations and the empirical correlations both require a density term to be included for flow rate calculations. Hence the air density was calculated using the ideal gas law together with local temperatures and pressures measured during the tests. A value of 1000 kg/m^3 was used for water density.

6.2 Empirical Wet Gas Flow Correlation Results

Figure 6.2 below shows the results obtained when using the single-phase dry equations (Eqn.2.1). Figure 6.2a is a linear regression fit of the actual (measured) gas mass flow rates against the predicted gas mass flow rates, whereas Figure 6.2b plots the relative measurement errors as a function of gas volume fraction (GVF).

These results show that this method grossly overestimates the gas mass flow rate in wet gas conditions. As illustrated by figure 6.2b the error on the dry gas mass flow rate is almost zero (at GVF=0), as the Venturi meter is operating within its calibration dry gas flow rates. However, as liquid is introduced this error increases progressively reaching over 100% as the liquid loading increased. The presence of liquid in the gas stream causes the differential pressure over the Venturi's throat to increase as a result of the changes in mixture density and multiphase flow related turbulence. This larger differential pressure results in larger calculated flow rates. The Venturi meter calibrated in dry gas conditions would of course read this as an additional gas flow rate.

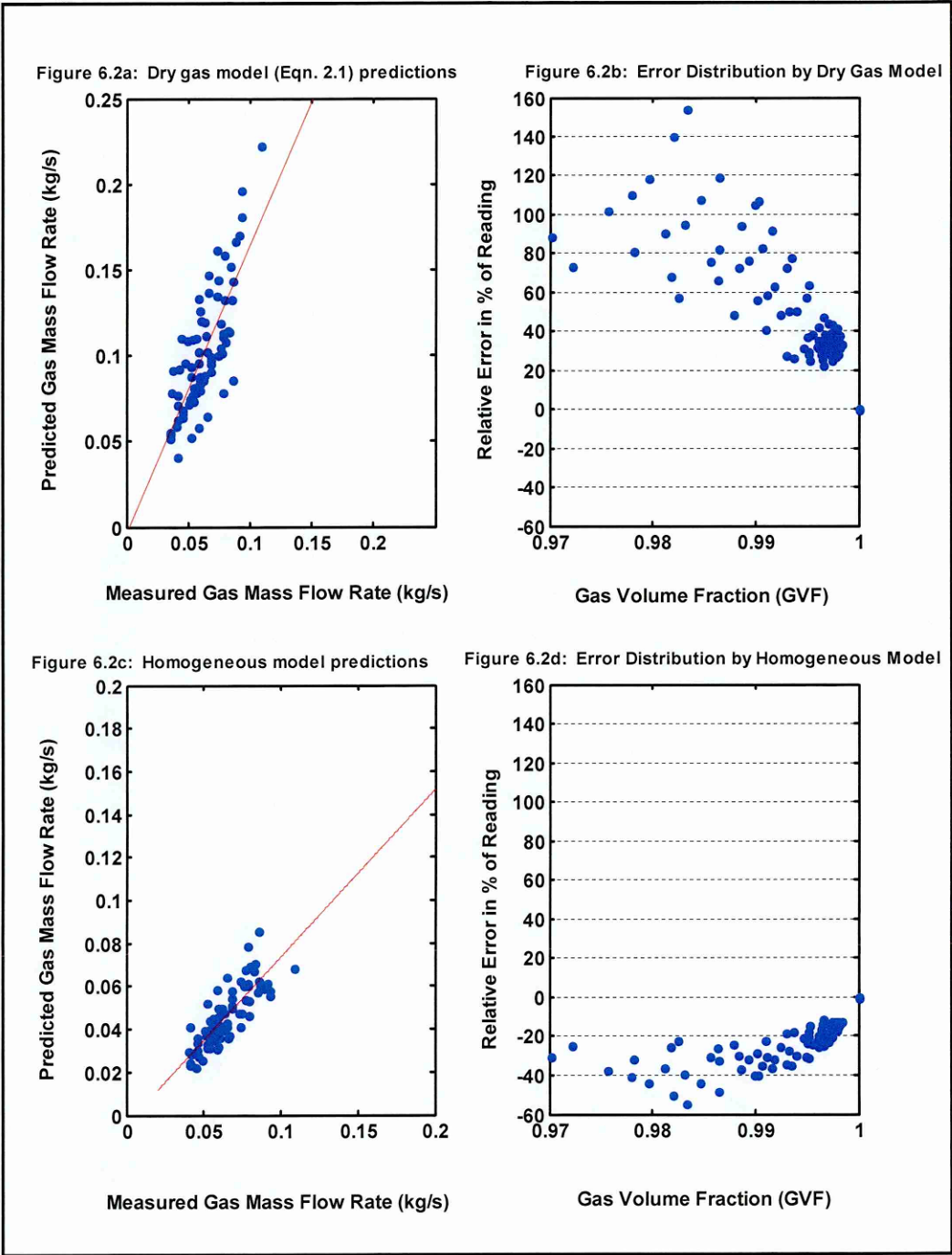
The above results clearly illustrate the effect of liquid loading on a Venturi meter previously calibrated with dry gas, and with no mechanism to account for over-reading errors caused by liquid loading. Hence it can be deduced that dry gas relationships are only valid for when single-phase conditions actually exist and cannot be directly applied to wet gas/multiphase flow measurements. This scenario can present itself in the production field, if operators are not aware of the liquid loading in wells previously defined as dry gas producing wells. This case can also occur, where

inefficient production separation allows significant liquid carry-over followed by metering of supposedly single-phase gas phase.

Given the above problems, when differential pressure meters are used for two-phase flow metering, corrections factors are proposed to account for the over-reading. One of the most basic of these correlations is the homogeneous model, which is purely analytical and assumes that the gas and liquid phases have the same velocities (Eqn.2.3). Figures 6.2c and 6.2d show the results obtained with the homogeneous model. As can be seen, this correlation achieves significantly better measurement results than the dry gas model, however, in doing so it goes to the other extreme and grossly under-estimates the gas mass flow rate as the GVF is reduced. The low operating pressure of the current data exacerbates the poor prediction result of this model further, where the gas to liquid density ratio is low. In fact, Steven (2001a) has shown that at higher pressures (20-60 bar); where the gas to liquid density ratio is significantly higher, the homogeneous model can perform better than some of the two-phase empirical flow correlations.

The results obtained by the homogeneous model in this current study conclude that even though the homogeneous model improves the Venturi dry gas model, it results with significant errors by under-estimating the gas mass flow rates. Hence the homogeneous model is not satisfactory to account for the errors caused by the liquid loading in wet gas conditions at low pressures.

Figure 6.2: Gas Flow Rate Predictions by Dry Gas and Homogeneous Models



The most well-known differential pressure two-phase correlation is that of Murdock (1962). Murdock's analysis, which ignores any interaction between the gas and liquid phases (momentum exchange), yields an equation, which attempts to correct the apparent reading to the actual (measured) value. This equation contains an empirically determined constant, M , which is equal to 1.26 for orifice meters.

The results of applying the Murdock equation to the current Venturi data appear in Figures 6.3a and 6.3b. It is evident from these results that the correction is insufficient to adjust the apparent reading to the actual reference values. This equation appears to perform better at higher liquid loading as indicated by the reduction in measurement errors as the GVF is reduced below 0.98. The poor prediction of the Murdock correlation could be attributed to the fact that it was developed for orifice meters operating in general two-phase flow and thereby may not be expected to perform well when considering annular/mist flow regime with Venturi meters.

The approach suggested by Jamieson and Dickinson (1993) was to adjust the value of M to fit the Venturi data. When the current data was plotted on a graph of $\sqrt{DP_p / DP_g}$ versus X (modified Lockhart-Martinelli Parameter), the slope of this curve, M was found to be 1.92 as shown in Figure 6.4.

The results obtained when using the modified Venturi Murdock constant, $M=1.92$ are shown in Figures 6.3c and 6.3d. A significant improvement can be seen with the use of this Venturi constant as compared with the orifice one, where the bulk of the data is now predicted to within $\pm 10\%$ measurement error. It is however clear that; even the refinement of the empirical constant does not wholly result with satisfactory measurement results.

These results indicate that M is not a universal constant and that refining empirical constants originally determined for orifice meters for Venturi meters may not be the best way forward in the search for improved flow rate measurement techniques.

Figure 6.3: Gas Flow Rate Predictions by Murdock Correlations

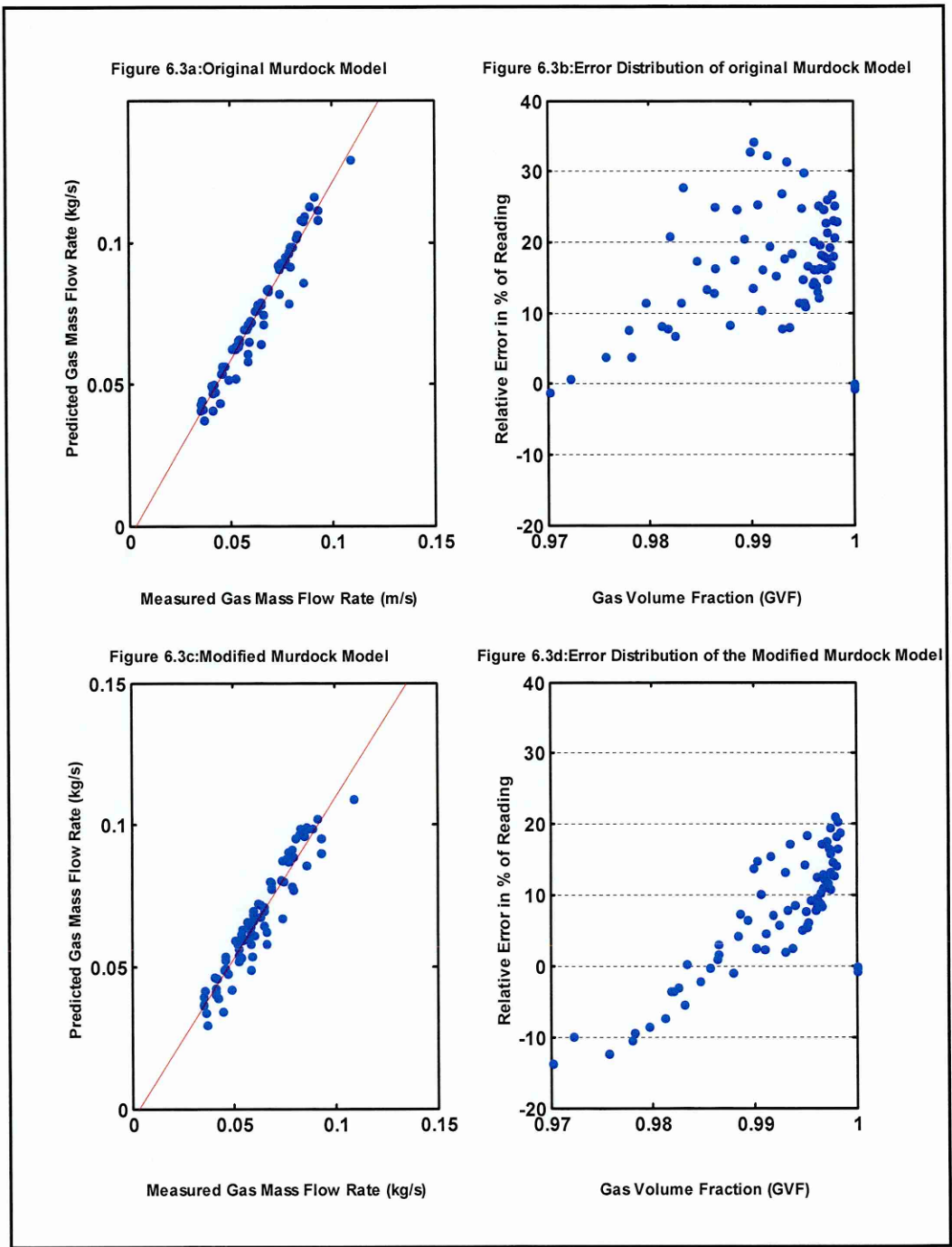


Figure 6.4: Determining the Murdock constant, M for the Current Venturi Data

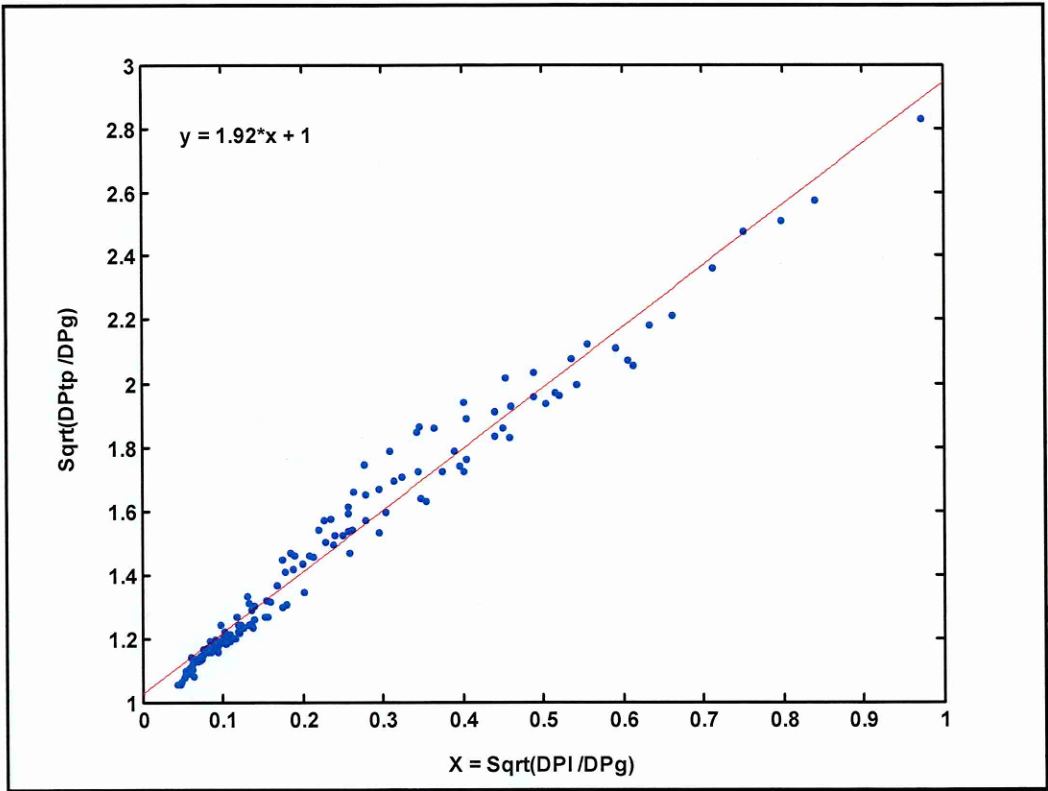


Figure 6.5 displays the performance results of Chisholm, Lin, and Smith and Leang correlations, using equations 2.5, 2.7 and 2.9 respectively. The Chisholm and Lin correlations show generally similar results to the original Murdock correlation. As for the Murdock correlation, the Chisholm and the Lin correlations were also developed from general two-phase flow through orifice plate meters, which may explain why these correlations are behaving similarly.

As liquid is introduced the measurement error appear to be increasing linearly, until a GVF of 0.98 is reached, at which point it starts to decline towards the point of no error. This similarity between the performance trend of these two correlations and their tendency for improved measurements as the GVF is reduced beyond 0.98 may suggest that these correlations are indeed more relevant to general two phase flow and cannot reliably meter the gas portion of high volume fraction multiphase flow (wet gas).

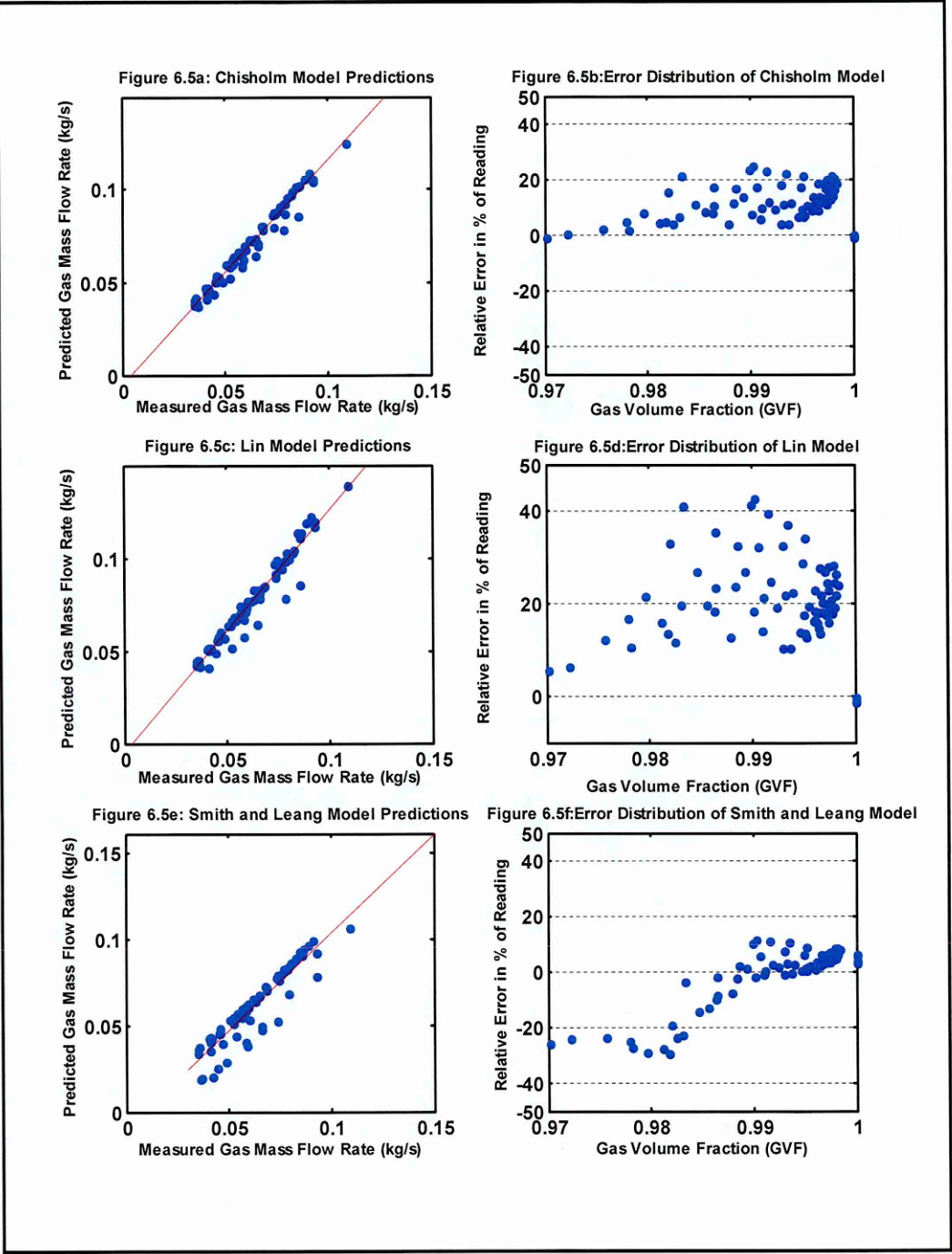
Figures 6.5e and 6.5f display the measurement results of Smith and Leang correlation. As well as an orifice meter, this correlation was formed by data covering Venturi and nozzle meters. Smith and Leang formed their correlation from a different approach to the problem of two-phase flow modelling than taken by the researchers mentioned above by introducing a blockage factor, which is a corrective factor applied to the single phase equation to account for the liquid flow partially blocking the flow of gas.

In contrast to the above correlations, the Smith and Leang correlation displays a peculiar trend as it experiences a sharp decline as the GVF is reduced below 0.99. The reason for the poor predictive results at GVF of less than 0.99 is due to the fact that the blockage factor is limited to mixture quality greater than 0.1, which is exactly where the measurement accuracy starts to deteriorate. The reason for achieving better results than other general two-phase flow correlations tested here, particularly for GVF greater than 0.99 could be said to be due to the fact that the development of this correlation was based on Venturi data in addition to orifice and nozzles.

It must also be mentioned that as the GVF goes to 1 (dry gas conditions), the Smith and Leang correlation does not give the expected dry gas calibration accuracy predictions, instead it over predicts the dry gas mass flow rate with a measurements. This is because at GVF of 1, the Blockage factor (denominator of Smith and Leang correlation) goes up to 1.05627 instead of unity, as it theoretically must to be correct.

From the above results, it may be concluded that, based on the current tests, the correlations of Murdock, Chisholm and Lin all appear to behave similarly and give generally better measurement results as GVF is reduced, in this case below 0.99, whereas the Smith and Leang correlation does better in the other end of this spectrum obeying its experimental applicability range.

Figure 6.5: Gas Flow Rate Predictions by Chisholm, Lin, Smith and Leang Models



Figures 6.6a to 6.6d display the results of de Leeuw (1997) and Steven (2002) respectively. These two correlations are the only published Venturi wet gas correlations. As explained in chapter 2, the form of the de Leeuw correlation is similar to the Chisholm correlation, except that de Leeuw accounts for both pressure and gas flow rate effects.

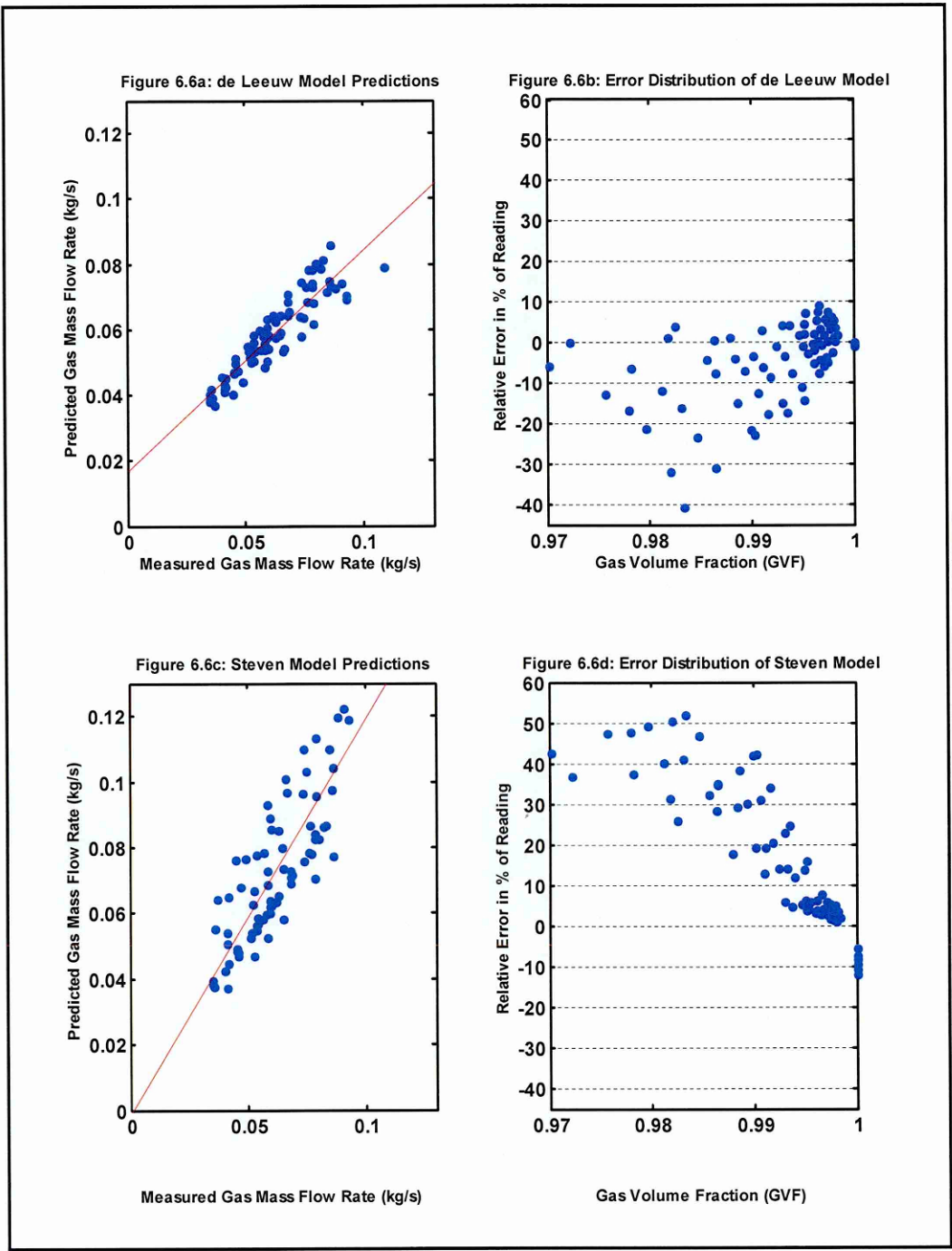
The de Leeuw correlation (Figures 6.6a and 6.6b) achieves the highest measurement accuracy of the tested flow correlations, with 78 % of the data predicted to within ± 10 %. The higher measurement errors were identified to be associated in the area of superficial liquid velocity greater than 0.25 m/s (see test matrix, Figure 6.1), which corresponds to higher liquid loading in the annular/mist flow regime.

Steven's correlation results are shown in Figures 6.6c and 6.6d. As can be seen the measurement errors of this correlation increase linearly with the decrease of gas volume fraction (GVF). The poor performance trends of both the de Leeuw and Steven's correlations under the current test conditions are primarily due to the fact that they are being used outside of their applicability range in terms of gas mass fraction (quality). The de Leeuw line pressures varied between 15 to 95 bars, whereas the Steven's tests ranged between 20 – 60 bars. These higher pressures result a higher gas mass fraction (quality) ranging from 0.5 to 1, which was not possible to obtain in the current study due to lower operating pressure (near atmospheric conditions).

As can be seen in Figure 6.6d, one fundamental problem with the Steven correlation is that as the GVF goes to 1, the denominator of this equation goes to 1.1095, leading to an average measurement error of ± 9 % in dry gas conditions. This observation is worse but similar in trend to that of Smith and Leang correlation in dry gas conditions.

The above results indicate that the de Leeuw and Steven's correlation should only be used in their experimental applicability ranges (quality of 0.5 and above) and that they cannot be extrapolated reliably to low pressure applications similar to the current test data.

Figure 6.6: Gas Flow Rate Predictions by de Leeuw and Steven Correlations

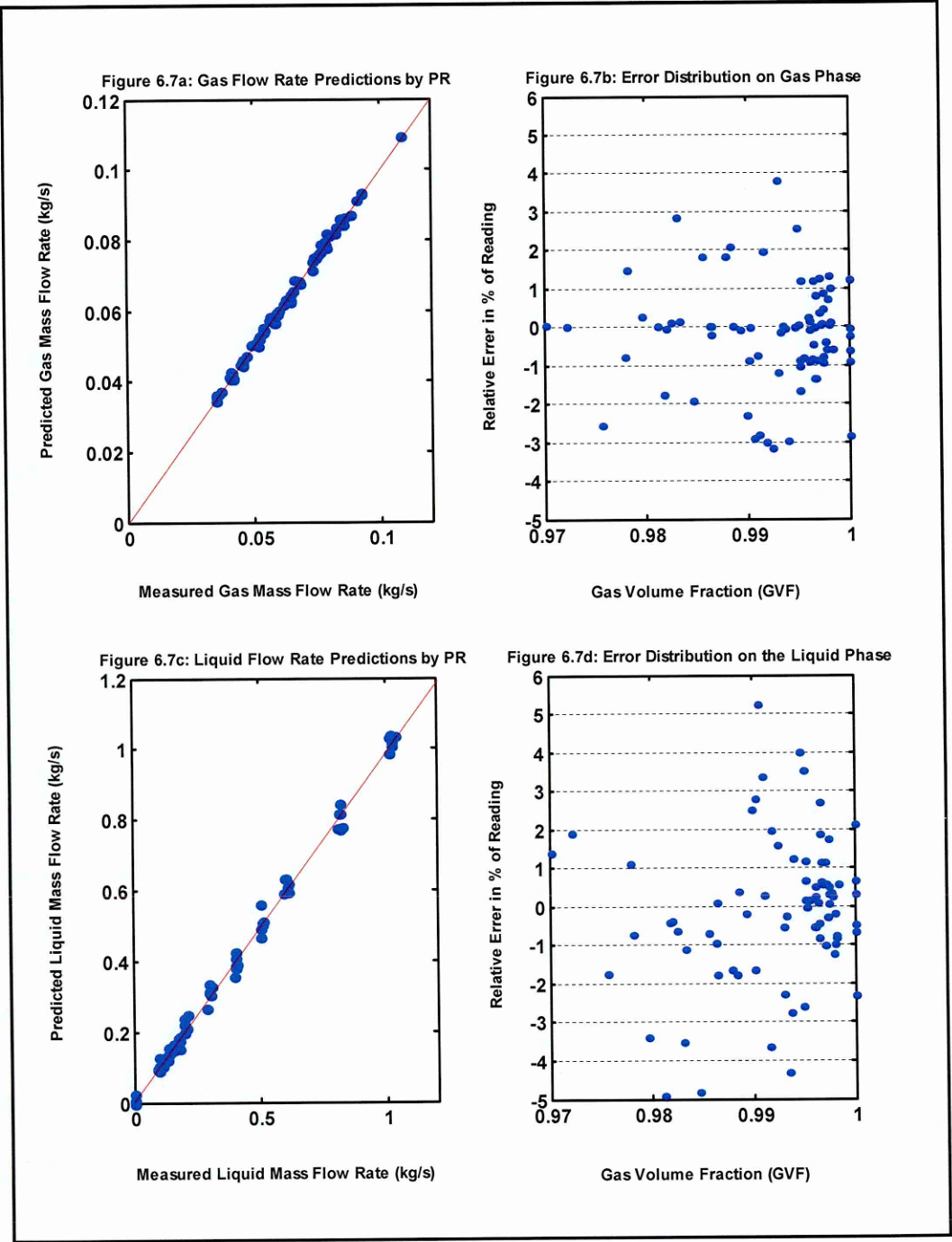


6.3 Bayesian MLP Neural Network Results

The measurement accuracies obtained by the use of the Bayesian MLP neural network is given in Figure 6.7 below. The results shown are for reproducibility cases, where the network is tested with previously unseen data, which is the same data as that tested with the above empirical flow correlations. Since the empirical flow correlations are using only the throat differential pressure (DP12) and the absolute pressure sensor (AP01) the PR system was also based only on the cross-sensor data fusion of these two sensors using amplitude feature vectors as they gave the best flow rate measurement results (see chapter 5).

As can be seen in Figures 6.7a to 6.7d, the neural network model achieves extremely good measurement results for both the gas and liquid phases with a measurement error of $\pm 5\%$ for both phases. One of the main advantages of pattern recognition based techniques is that unlike empirical correlations, it allows the simultaneous measurement of gas and liquid flow rates, without prior knowledge of either phase. Furthermore the neural network model detects the presence of liquid (Figure 6.7c and 6.7d) in wet gas conditions. In other words in all the dry gas conditions the network models predicts both the gas and liquid velocities, with a GVF of between 0.9999 and 1, which indicates that for all practical purposes this a dry gas condition and that there is no liquid production as yet. However, as liquid is introduced and thereby GVF is reduced the network is able measure the liquid flow rates accurately.

Figure 6.7: Gas and Liquid Flow Rate Predictions by Bayesian MLP Model



6.4 Comparison between PR and Empirical Flow Correlation Performance

In order to get a feel of how the different models fair against one another the Root Mean Square (RMS), fraction deviation, d, was computed for each correlation using equation (2.43), and the results are summarised in Table 6.2 below. Note the smaller the value of “d” the higher the accuracy of the correlation.

Table 6.2: Root Mean Square Fractional Deviation (d) Results for Gas Mass Flow Predictions.

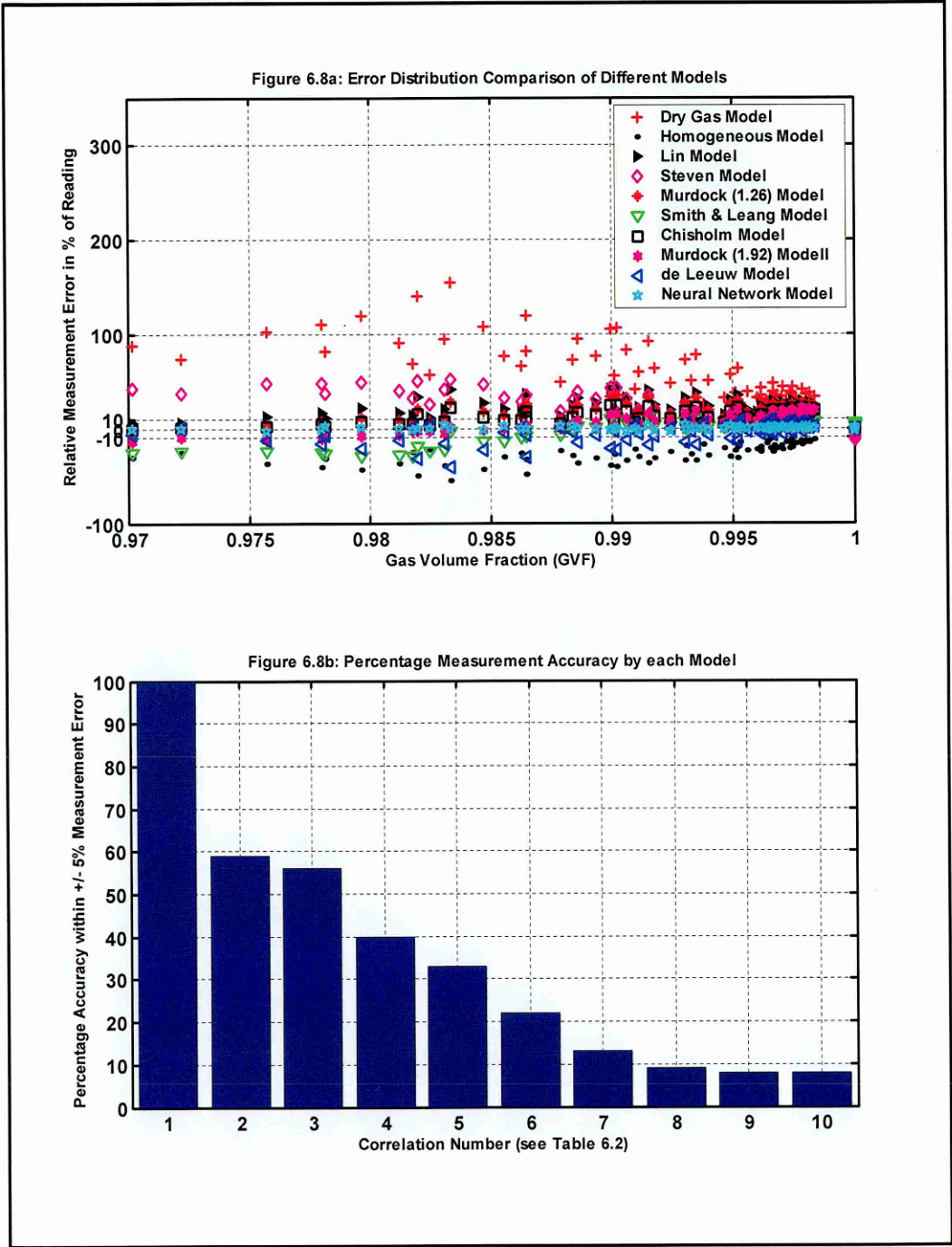
No.	Correlation Used	Root Mean Square Fractional Deviation (d)
1	Pattern Recognition Neural Network	0.0462
2	De Leeuw	0.1047
3	Murdock (M=1.92)	0.1232
4	Chisholm	0.1397
5	Smith and Leang	0.1517
6	Murdock (M=1.26)	0.2003
7	Steven	0.2264
8	Lin	0.2460
9	Homogeneous	0.3188
10	Venturi dry gas equation	0.7249

Based on the RMS Fractional Deviation, d across the whole 78 test data points, the Pattern Recognition model, achieves by far the best prediction accuracy, followed by the de Leeuw correlation. As should be expected, the Venturi single-phase equation and the homogeneous equations achieve the worst results.

Figure 6.8 summarises the measurement results of all the 10 correlations, and shows that the case of no correction factor (dry gas model) and the homogeneous model perform the least, while the neural network model achieves the best measurement results. The correlations were also compared in terms of percentage accuracy that fell within $\pm 5 \%$ (Figure 6.8b). The neural network again meets this criterion by

measuring all the test points within the specified error band. The de Leeuw, Smith and Leang and the Steven correlation follow this lead by achieving 59, 57 and 40 % respectively.

Figure 6.8: Summary of Comparative Results by Different Correlations



6.5 Conclusions

The conclusions from this chapter can be summarised as follows: -

1. Venturi meters calibrated in dry gas conditions significantly overestimate the gas mass flowrate and should not be used for wet gas flow measurements, as the dry gas relationship is only valid when single-phase conditions exist.
2. The homogeneous model grossly underestimates the gas mass flow rate particularly as the GVF is reduced. The poor prediction accuracy of this model here is also exacerbated by the use of the current low-pressure data, where the gas to liquid density ratio is low.
3. Empirical correlations have a range of applicability, which must not be exceeded if accurate gas flowrate measurements are to be expected.
4. The correlations developed from the orifice plate meters (Murdock, Chisholm and Lin) for general two-phase flow appear to behave similarly as they give better measurement accuracy as the GVF is reduced. It was shown that it is possible to achieve better measurement accuracy by refining the empirical constants within the correlations, using the Murdock correlation by way of example.
5. The Smith and Leang correlation performs well within its applicability range. The blockage factor in this correlation is limited to a mixture quality greater than 0.1, which corresponds to a GVF of 0.988 for the current test data. Below this blockage factor range, the accuracy of this correlation deteriorates. Another problem with this correlation is that it overestimates the calibrated dry gas flow rates, due to the fact that as the GVF goes to 1, the blockage factor goes to 1.05627.

6. Amongst all the empirical correlations tested here, the de Leeuw correlation improved most the Venturi over-reading prediction and achieved the highest measurement accuracy with 78 % of the data predicted to within ± 10 %.
7. The Steven Correlation significantly overestimates the two-phase gas mass flow rate. It was observed that for gas qualities closer to 0.5, that this correlation gave a good prediction with measurement accuracy within ± 10 %. Similar to the Smith and Leang correlation, the Steven correlation also does under-predict the dry expected measurement accuracy. This is caused by the denominator of this equation going to 1.1095, instead of 1 in dry gas conditions.
8. The pattern recognition neural network models appear to outperform the empirical correlations across the whole test conditions when using the amplitude features of the sensor fusion. The main reason for this is, because the pattern classifier is performing in interpolation mode.
9. The pattern recognition model system measured 100 % of both the gas and liquid mass flowrates were predicted to within ± 5 of the measured values.
10. Unlike empirical correlations, which have no means of knowing the liquid flow rate, the pattern recognition system is able to detect the presence and measure the amount of liquid in wet gas flow conditions as well as providing real time simultaneous measurement of gas and liquid flow rates, without prior knowledge of either phase.

CHAPTER 7

CONCLUSIONS AND FUTURE WORK

While the use of Venturi meters is not new, its use with advanced pattern recognition techniques has resulted in a completely novel wet gas measurement system, enabling the detection of liquid presence in wet gas flow conditions and the simultaneous measurement of gas and liquid flow rates without the need for preconditioning of the flow or prior knowledge of either phase. The measurement system consists of a classical Venturi tube with two pressure sensors located in the conventional positions (DP12 and AP01) and one extra differential pressure sensor over the axial Venturi pressure recovery length (DP13), see Figure 3.3 for the locations of the pressure sensors. In dry gas flow conditions, the system can be switched to the standard dry gas Venturi equations to calculate the gas flow rates. However in wet gas flow conditions, where the dry gas flow equations breakdown, the pattern recognition system can be activated to measure both the liquid and gas flow rates in a Venturi-PR combination approach (as depicted in Figure 5.1).

For its measurement approach, the pattern recognition system developed in this work relies on pressure sensors to extract relevant information in the form of features. A Bayesian multi layer perceptron (MLP) neural network is then used to relate these features to the gas and liquid superficial velocities, from which the volumetric flow rates can be calculated.

The flow regimes studies here covered four main flow regimes. These were dry gas flow conditions, annular/mist flow, wavy flow and slug flow regime. Although the main focus of this study lie in the annular/mist flow regime because of its dominance in wet gas flow conditions, nevertheless it is necessary to widen the scope to include the neighbouring flow regimes, as they can develop in the production system during the production life of the well.

The following conclusions can be drawn from the work conducted in the current study.

7.1 Conclusions from the Current Work

1. Digital signal processing techniques were used, which enable the extraction of vast amount of features from the Venturi pressure sensors both in time and frequency domains. A number of features were subsequently found to be more effective than others, based on their discriminatory trend to the variations in flow conditions as well as their classification accuracy when used for flow rate measurement.
2. The features found most effective in this work were 6 amplitude features, 6 linear prediction coefficients (LPC) and 5 line spectral frequencies (LSF). Of the three feature domains, the amplitude feature vectors were consistently found to lead to better classification accuracies.
3. Further dimensionality reduction to the extracted feature vectors was not found useful in this work as it resulted in reduced pattern recognition measurement accuracies. Subsequently the discriminatory ability of each feature vector and the classification accuracy resulting from it was evaluated for each pressure sensor.
4. A number of training algorithms for multi layer perceptron (MLP) neural networks were evaluated initially. The Bayesian MLP neural network was found most effective when different network generalisation accuracies were compared. An added advantage of the Bayesian MLP neural network is that unlike traditional MLP neural networks, which require a dedicated validation subset to minimise overfitting, the Bayesian technique controls model complexity (overfitting) automatically using only the training data. Furthermore the Bayesian approach eliminates the guesswork required in determining the optimum number of hidden neurons and consistently leads to good networks that are not over-trained. Hence in this work a two layer Bayesian MLP neural network was used, having 10

neurons in the hidden layer and two neurons in the output layer. A sigmoid non-linear transfer function was used in the hidden layer and a linear transfer function in the output layer. The structure of the network was kept constant through the study, with the only variable being the size of the input nodes, which is directly controlled by the type of feature vectors used. This allowed an objective methodology to be developed upon which the performance of different pressure sensors and feature vectors could be compared.

5. When only the Venturi throat differential pressure (DP12) was used, the amplitude feature vectors achieved overall a better measurement consistency and accuracy in all the flow regimes studied than the linear prediction coefficients and the line spectral frequencies. In particular the amplitude feature vectors obtained 100 % in the zero liquid flow (simulating the detection of the absence of liquid flow in dry gas conditions) and the dry gas flow rates as well as liquid flow rates in the slug flow regime. The line spectral frequencies have been found in this work to lead consistently to better classification accuracy of the individual gas and liquid flow rates in different flow regimes than the linear prediction coefficients.
6. In the case where only the differential pressure across the Venturi recovery length (DP13) was utilised, it was that the amplitude feature vectors achieved overall a better measurement accuracy and consistency than the linear prediction coefficients and line spectral frequencies. The amplitude feature vectors led to 100 % measurement accuracy in the confirmation of the absence of liquid flow in dry gas flow conditions and also the measurement of gas flow rates in the slug flow regime.
7. When only the absolute pressure sensor was used, it was the sensor feature fusion that achieved the best measurement accuracy and consistency in performance in all the flow regimes studied, and did so more for the measurement of the liquid flow rates than the gas flow rates. Unlike the Venturi recovery length differential

pressure sensor, feature fusions scenario has resulted in a 100 % prediction of flow rates in the zero liquid identification in the dry gas flow conditions and for the liquid flow identification in the wavy flow regime. However, if only the individual feature vectors were compared, then the amplitude feature vectors had consistently performed better than linear prediction coefficients and the line spectral coefficients.

8. The individual sensor performance and the improvements in some cases of the feature fusion scenarios have indicated that further flow rate measurement improvements could be achieved with cross-sensor feature fusion. The most effective way of achieving cross-sensor feature fusion was found by combining each feature domain across the three pressure sensors. This has led to the identification of the best feature vectors for the measurement of the gas and liquid flow rates across the whole flow domain of interest.
9. The cross-sensor data fusion has shown that the fusion of the amplitude feature vectors of the three sensors have achieved the best overall measurement accuracy by obtaining 100 % prediction of both gas and liquid flow rates to within a measurement error of better than ± 5 %. The amplitude features of the Venturi throat differential pressure sensor and the absolute pressure sensor, which achieved measurement accuracy of 98 % and 97 % for the liquid and gas flow rates respectively across the whole flow domain, closely followed this. The third best measurement accuracy was achieved by the fusion of the amplitude feature vectors of the throat differential pressure and the recovery length differential pressure sensor. The cross-sensor data fusion results confirmed that the best flow discriminating feature vectors were by far the amplitude features and that the cross-sensor data fusion would significantly enhance the measurement accuracy of the classifier.
10. The flow rate measurement results by different feature vectors showed that the metering system developed in this study is affected by the changes in flow

regimes. However, at the same time, the results showed that if sufficient calibration data is provided in the neighbouring flow regimes to the wet gas flow region then the system could be made independent of flow regime. In other words, the same pattern recognition model and feature could be used in the entire different flow regime, provided the system was calibrated for this purpose at design stage.

11. The results presented by this research demonstrated the potential application of the developed pattern recognition techniques as a diagnostic technique for the detection of liquid break-through in wells or transportation pipelines previously defined as dry gas flow systems. In an operational environment, the liquid volume fraction (LVF) predicted by the pattern recognition system can be used as a monitoring parameter. Beyond a given threshold of LVF (e.g. ≥ 0.001 %) the flow system would be considered as wet gas and the pattern recognition system would provide both the gas and liquid flow rates online.
12. The results from the study of flow regime effects showed that if substantially novel data is presented to the network (as represented by introducing new flow regimes here) then it will be prone to significant errors.
13. The analysis of the operating line pressure effects showed when the system was allowed to operate in extrapolation mode, whereby it was trained with input data from 1 bar and tested with data from three bar, the network classification accuracy was very poor. However when the system was operated in interpolation mode by training the system with data from 1 bar and 3 bar, while testing it with data from 2 bar, the measurement accuracies were significantly improved.
14. The performance of the Venture-pattern recognition system (Venturi-PR) developed here was tested against the empirical correlations developed for two phase (gas-liquid) flow and deemed applicable to wet gas flow measurements.

15. Venturi Meters calibrated in dry gas conditions significantly overestimate the gas mass flow rate and should not be used for wet gas flow measurements, as the dry gas relationship is only valid when single-phase conditions exist.
16. The homogeneous model grossly underestimates the gas mass flow rate particularly as the GVF is reduced. The poor prediction accuracy of this model here is exacerbated by the use of the current low-pressure data, where the gas to liquid density ratio is low.
17. Amongst all the empirical correlations tested here, the de Leeuw correlation reduces most the Venturi over-reading prediction and achieved the highest measurement accuracy with 78 % of the data predicted to within ± 10 %. Although the operating line pressure was significantly higher (15-90 bar) than the operating pressure of the current study, there was however considerable overlap in terms of Froude number (i.e. gas velocity), which is probably why the correlation performed better than other correlations in the test.
18. The Steven Correlation significantly overestimates the two-phase gas mass flow rate especially as the GFV is reduced. It was observed that for gas qualities closer to 0.5 that this correlation gave a good prediction with measurement accuracy within ± 10 %.
19. The correlations developed from the orifice plate meters (Murdock, Chisholm and Lin) for general two-phase flow appear to behave similarly with significant over-estimation of the gas mass flow rate. It was shown that it is possible to improve the measurement accuracy by refining the empirical constants within the correlations, using the Murdock correlation by way of example.
20. The pattern recognition neural network models appear to outperform the empirical correlations across the whole test conditions as it was able to measure 100 % of

both the gas and liquid mass flowrates were predicted to within ± 5 of the measured values.

21. Unlike empirical correlations, which have no means of knowing the liquid presence, the pattern recognition system is able to detect the presence and measure the amount of liquid in wet gas flow conditions as well as providing real time simultaneous measurement of gas and liquid flow rates, without prior knowledge of either phase.

Having summarised above the main findings of the current work, below are recommendations of some further enhancements suggested for the current work.

7.2 Future Work

The current research work can be further extended in the following key application areas.

1. One of the most important sources of errors in neural network applications arises from novel input data. As was seen in chapter 5, a network, which is trained to discriminate between numbers of classes coming from a set of distributions, will be confused when confronted with data coming from an entirely new distribution. This was most evidently demonstrated when the current pattern recognition system was trained only on annular/mist flow data, and then tested with data coming from slug flow and other flow regimes (see chapter 5). The degree of inaccuracy depends on the distance between the new input feature vectors and the nearest training patterns. It would be useful for the system to output along with the classification of input data, a measure of confidence of this decision or to refuse to make a decision if the input data is found to come from a completely new class (e.g. slugging conditions in a wet gas transportation pipeline or a significant change in pipeline operating pressure).

There are a number of publications dealing with the subject of novelty detection using pattern recognition techniques in the literature, but perhaps the most relevant of these to the context of the current work is that of Bishop (1995b). He considered probability density estimation of neural network output as a measure of novelty. Probability density functions describe the frequency of occurrences of an observation that occur in any point within a domain of interest. Bishop (1995b) implemented the novelty detection technique by estimating the probability density of the training data thus modelling its distribution and checking whether an input data point comes from this distribution. He modified the training error minimisation algorithm, such that goal of the network training is to find a good approximation to the regression by minimisation of a sum-of-squares error defined over a finite training set. It is expected that this approximation will be most accurate in regions of input space for which the density is high, since then

does the error function penalise the network mapping if it differs from the regression. If the data falls in a region with high density then it is likely that the data point comes from a class that is not represented by the training data and it is likely that the network will perform poorly. This can be used to assign error bars to the network outputs or by placing threshold; new feature vectors that fail the threshold may be rejected. In this work the probability density estimation was done on the input data using a kernel-based estimator with gaussian kernel functions. Similar approach to the above can be considered as a possible extension of the current work for the detection of the development of new flow conditions in previously wet gas flow calibrated measurement system. In practical applications the operator can be alerted if substantially new conditions that fail the threshold are developing in the production/pipeline system and the system switched into a retraining mode, while the classifier can simply reject sporadic feature vectors that fail the threshold.

2. Other pattern recognition techniques could also be explored including the integration of MLP neural networks with fuzzy logic models to overcome the problem experienced by MLP neural network when completely novel data is presented to the system as fuzzy logic models are better suited for detection purposes and defining class boundary conditions. In this regard several MLP neural networks could be developed for different flow condition with the fuzzy logic models generating the class boundaries and deciding which MLP neural network to use for which flow condition (e.g. for dry gas conditions, annular/mist, slug flow, etc).
3. Although extensive feature vectors were tested in this study, however there are other feature vectors that could be evaluated for their effectiveness including reflection coefficients (RC), log area ratio (LAR), arcsine of reflection coefficients (ASRC), impulse response of LP synthesis filter (IR), etc. In addition the effectiveness of other flow sensors could also be explored in wet gas flow conditions such dielectric sensors, gamma densitometers and microwave sensors.

4. The present research work was conducted at near atmospheric conditions using air/water as the test fluids. The pattern recognition techniques developed in this work proved extremely successful in these conditions. However to make the techniques relevant at real world, gas/condensate field condition level, it would be necessary to repeat the tests at higher pressures (15-90 bar) and if possible using natural gas and condensate fluids (or nitrogen and kerosene). In this regard the pattern recognition system developed in this work in terms of optimum features, sensor combinations and Bayesian MLP neural network can be utilised with the only change being the operating conditions.
5. For a typical wet gas producing well, the water content of the liquid phase will increase over time. It is then important to monitor the water content on-line in order to detect water break-through in the reservoir. In addition, in gas lift operations where there is an economical value in the recovery of the liquid phase, there is a need to know the amount of liquid produced as well as the watercut of the liquid phase. Hence it would be useful to extend the present work to three-phase gas-oil-water metering system.
6. The evaluation of the scalability of the present system to other pipeline sizes and the effect of different Venturi beta ratios will also be necessary to contribute toward building a general flow metering system. It is anticipated that both pipeline diameter change and Venturi beta ratio will affect the pattern recognition metering accuracy. However this problem can largely be circumvented by the provision of suitably general training set spanning the full range of conditions likely to be encountered in practice.
7. The performance and effect of Venturi orientation in vertical upward flow should also be considered. Vertical orientations would produce a more symmetric flow than horizontal ones since the gravitational force component now acts along the

pipe axis. The reduced slippage between the phases may result in reduced feature discriminatory ability, but it would be extremely important to verify this.

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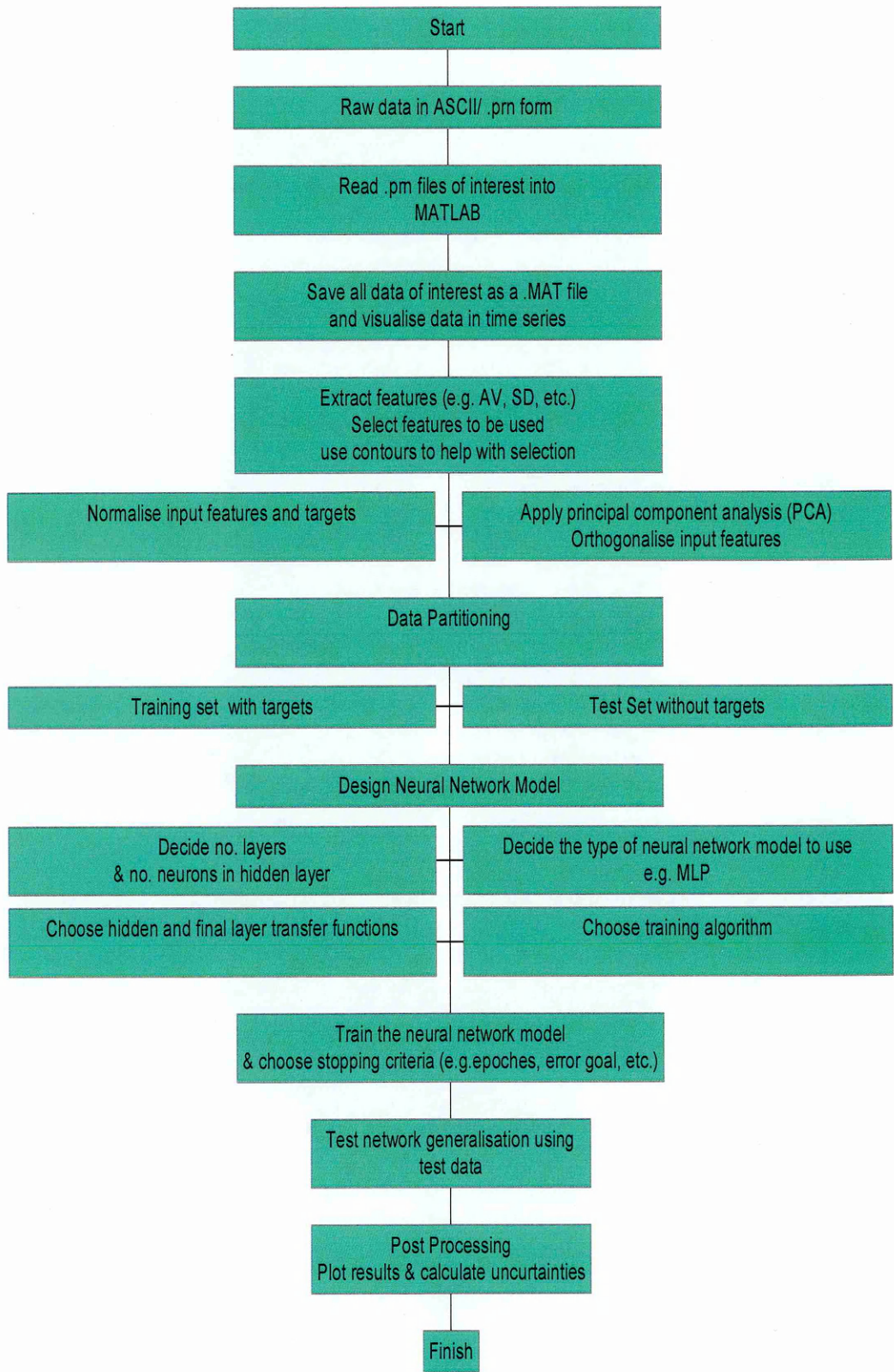
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APPENDIX A: MATLAB Scripts

The following appendix A contains MATLAB programs (e.g. importing data into MATLAB, data pre-processing, feature extraction and selection and neural network models. The below flow chart illustrates the typical workflow developed in this research for data analysis and simulation using MATLAB programming language.

Figure A.1: Logical Flow Chart for Data Analysis & Programming



THE FOLLOWING PROGRAM READS ASCII FILES INTO MATLAB

```

fnames = {'Wavy_AnnularMist Flow_A','Wavy_AnnularMist Flow_B','Wavy_Annula
st Flow_C','Wavy_AnnularMist Flow_D','Wavy_AnnularMist Flow_E',...
        'Slug_AnnularMist Flow_A','Slug_AnnularMist Flow_B','Slug_Annular
st Flow_C'};

Here we're entering the experimental data with their test log names into M
ALB. These are 8 files each containing 32 test data records (i.e.256 two
phase data points).

N=32;
ext = '.prn';
Nl=1;
for i =1:length(fnames)
    for j=1:N
        thisfile = [fnames{i}, num2str(j), ext]; %Construct filename
        % This textread writes each files data to the next column in a mat
%.
        [TimeT(:,1),FM11T(:,1),FM12T(:,1),FM15T(:,1),PT01T(:,1),TT01T(:,1),
DP11T(:,1),DPRT(:,1),AP01T(:,1),DP12T(:,1),DP13T(:,1)]=textread(thisfile,'
%f %f %f %f %f %f %f %f %f %f','headerlines',11);
        Liquid_rate1(col)=mean((FM12T)/1000);%q in m3/s
        Liquid_rate2(col)=mean((FM11T)/1000);%q in m3/s
        Gas_rate(col)=mean((FM15T)/1000); %q in m3/s
        PT1(col)=mean(PT01T)*100000; % convert the PT01 data from bara to Pa
        TT1(col)=mean(TT01T)+273;
        AP1(col)=mean(AP01T)*100000;
        TS1(col)=mean(TS01T)+273;
        AV1(col)=mean(DP12T);
        AV2(col)=mean(DP13T);
        col=col+1;
    end
end

```

The above program reads ASCII (.prn) data into MATLAB, so that for exampl
all the data from DP12 will be read into one 3251x256 matrix and so on.
in order to reduce the computer processing requirements, then each sensor
data can be saved as a .MAT file.

d onobar_twophase_velocity % This .MAT file contains 2-phase superficial
 locities of gas and liquid at 1 bar.
 d complete_twophasedata; %This .MAT file contains sensor'data i.e. DP1
 DP13, AP01, etc.
 milar procetures were carried out for single-phase data and feature extr
 ion.

Extracting Linear Prediction Coefficients from DP12, DP13 and AP01

```
e]=lpc(DP12,5);          [a1,e1]=lpc(DP13,5);          [a2,e2]=lpc(AP01,5);
);
real(a)';                a1=real(a1)';                a2=real(a2)';
e';                      e1=e1';                      e2=e2';
    a1 and a2 are matrices containing linear prediction coefficients extrac
d from DP12, DP13 and AP01 respectively.
```

Extracting Line Spectral Frequencies for DP12

```
= 0;
F = {};
Because LPC are stored in a MATRIX form have to input each column of a to
poly2lsf seperately. Return lsf as a cell array.
while i < size(a, 2)
    i=i+1;
    lsf{i} = poly2lsf(a(:,i));
end
F_DP12=[lsf{1:128},lsf{129:256}];
```

Extracting Line Spectral Frequencies for DP13

```
= 0;
F1 = {};
input each column of a to poly2lsf seperately. Return lsf as a cell array
while i < size(a1, 2)
    i=i+1;
    lsf1{i} = poly2lsf(a1(:,i));
end
F_DP13=[lsf1{1:128},lsf1{129:256}];
```

Extracting Line Spectral Frequencies for AP01

```
= 0;
F2 = {};
input each column of a to poly2lsf seperately. Return lsf as a cell array
while i < size(a2, 2)
    i=i+1;
    lsf2{i} = poly2lsf(a2(:,i));
end
F_AP01=[lsf2{1:128},lsf2{129:256}];
```

Extracting Amplitude Features

```
tr=mean(DP12); SDtr=std(DP12); CVtr=(SDtr./AVtr); Cstr=skewness(DP12); Ckt
kurtosis(DP12);
rec=mean(DP13); SDrec=std(DP13); CVrec=(SDrec./AVrec); Csrec=skewness(DP13)
Ckrec=kurtosis(DP13);
```

```

b=mean(AP01); SDab=std(AP01); CVab=(SDab./AVab);Csab=skewness(AP01);Ckab=
rtosis(AP01);
DP12(:,i);
)=(sum(xn.^2)/length(xn)); %total energy of the DP12 signal
=DP13(:,i);
)=(sum(xn1.^2)/length(xn1)); %total energy of the DP13 signal
=AP01(:,i);
)=(sum(xn2.^2)/length(xn2)); %total energy of the AP01 signal

ature Analysis by Contouring
split the Vsg data into sampled sets
age = [[1;ind+1],[ind;length(Vsg)]];
alculate the number of sampled sets
nlines = size(range,1);
= 6:30; % range of superficial gas velocity
= zeros(1,nlines);
= zeros(nlines,length(xi));
(k=1:nlines)
x = Vsg(range(k,1):range(k,2));
y = Vsl(range(k,1):range(k,2));
z = pn(range(k,1):range(k,2));
zi(k,:) = interp1(x,z,xi);
yi(k) = mean(y);
d
Below we've chosen linearly spaced vector, including minimum and maximum ✓
d with 15 levels of contours.
,h]=contour(xi,yi,zi,linspace(min(AVtr),max(AVtr),15),'-k');
abel(c,h)
ld on
ot(Vsg,Vsl,'ok','MarkerFaceColor','k')
abel('Superficial Gas Velocity, m/s'),ylabel('Superficial Liquid Velocit ✓
m/s');
cle('AVtr Feature of Throat DP');
ld off
    
```

NATURE PRE-PROCESSING

Normalise input training data and targets

```
p_input=[AVtr;SDtr;CVtr;Cstr;Cktr;AVrec;SDrec;CVrec;Csrec;Ckrec;AVab;SDab;Cvab;Csab;Ckab];
```

p contains the input data; in this case amplitude feature vectors, but similar setup can be done for feature combinations.

```
[Q]=size(p);
```

```
train_data=[1:2:Q];
```

```
test_data=[2:2:Q];
```

```
all=[Vsl;Vsg];
```

```
t_all(:,train_data);
```

```
p_input(:,train_data);
```

One way of normalising input features is by allowing them to fall in the range of [-1,1];

```
p, minp, maxp, tn, mint, maxt] = premnmx(p, t);
```

Another way of normalising is to apply zero mean and unity standard deviation as shown below.

```
p, meanp, stdp, tn, meant, stdt] = prestd(p, t);
```

A 3rd possibility of normalising data is to apply Principal Component Analysis (PCA)

```
[trans, transMat] = prepca(pn, 0.01);
```

Constructing Neural Network Model and Training

```
ptr = ptrans; ttr = tn;
```

```
net = newff(minmax(ptr), [10 2], {'logsig' 'purelin'}, 'trainbr');
```

above line constructs a MLP model with 10 neurons in the hidden layer and 2 neurons in the output layer.

Logsig logarithmic sigmoid transfer function in the hidden layer and a linear transfer function in the output layer.

```
net = init(net); % initialise network weights
```

```
net.trainParam.epochs = 2000; % note the stopping criterion can simply be a fixed number of iterations, i.e. epochs
```

```
net.trainParam.show = 100; % NaN if don't want to show;
```

```
net.trainParam.goal = 0.001; % 0.001; % This is also another stopping criterion
```

```
[net, tr] = train(net, ptr, ttr); % the training record tr contains information about the progress of the training
```

TEST DATA: After the model is being trained it can then be tested using a separate test data.

```
p_test_input(:, test_data);
```

```
t_test_all(:, test_data);
```

NETWORK OUTPUTS

```
an = sim(net, ptr); % Simulate/test the trained network. an corresponds to the normalised targets tn (note: in this line
```

we're testing the network with the same training to test its reproducibility).

```
poststd(an, meant, stdt); % Convert the network outputs back into the original units i.e. m/s
```

POST TRAINING ANALYSIS (postreg)

```
    i=1:2 % Because we had two targets  
    figure (i);  
    [m(i),b(i),r(i)]=postreg(a(i,:),t(i,:)); %m=slope, b= intercept and r=correlation coefficient.
```

APPENDIX B: DETAILS OF CD CONTENTS

The companion CD of this PhD thesis contains the following materials: -

Note: The Gamma Densitometry was not used in this work as it malfunctioned during initial tests. The readings of the Radial d.p didn't give any repeatable results during analysis and simulation hence it was also excluded from further analysis.

1) Experimental data folder contains the data files in Table B.1:

Table B.1: Experimental Data Files

File(s) Name	Data Points	Flow Regime	Pressure [bara]	V_{sg} [m/s]	V_{sl} [m/s]
Single_Phasegas1-16.prn	16	Gas	1	6-30	0
Single_Phasegas_at2bar1-9.prn	9	Gas	2	6-24	0
Single_Phasegas_at3bar1-8.prn	8	Gas	3	6-20	0
Wavy_AnnularMist Flow_A1-A32.prn	32	Wavy and Annular/Mist	1	6-30	0.05 and 0.06
Wavy_AnnularMist Flow_B1-B32.prn	32	Wavy and Annular/Mist	1	6-30	0.07 and 0.08
Wavy_AnnularMist Flow_C1-C32.prn	32	Wavy and Annular/Mist	1	6-30	0.09 and 0.1
Wavy_AnnularMist Flow_D1-D32.prn	32	Wavy and Annular/Mist	1	6-30	0.15 and 0.2
Wavy_AnnularMist Flow_E1-E32.prn	32	Wavy and Annular/Mist	1	6-30	0.25 and 0.3
Slug_AnnularMist Flow_A1-A32.prn	32	Slug and Annular/Mist	1	6-30	0.4 and 0.5
Slug_AnnularMist Flow_B1-B32.prn	32	Slug and Annular/Mist	1	6-26	0.6 and 0.7
Slug_AnnularMist Flow_C1-C32.prn	32	Slug and Annular/Mist	1	6-24	0.8, 0.9 and 1
Twophase Flow_at2bar1-28.prn	28	Annular/Mist	2	8-20	0.07, 0.1, 0.2 and 0.3
Twophase Flow_at3bar1-25	25	Annular/Mist	3	8-18	0.07, 0.1, 0.2 and 0.3

2. Simulation Results Folder Contents

- a. Complete test matrix: these are the calculated superficial gas and liquid velocities at 1 bar (272 data in total).
- b. Results of the neural network and empirical flow correlation predictions. The results included here are the optimum case results from chapter 5 (i.e. using amplitude feature vectors of DP12-DP13-AP01) and refer to the 122 test data points, which are previously NOT seen by the network. This file also contains the results of correlation comparison as detailed in chapter 6.

3. The CD also contains the complete PhD thesis in .PDF format.