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Pattern Recognition Techniques for Horizontal and Vertically Upward Multiphase Flow Measurement

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1 INTRODUCTION

Multiphase metering is an exciting solution to the growing production measurement issues in the Petroleum Industry today. Oil and gas production operations is occurring in more remote locations and deeper water depths (e.g. BP's PSVM Block-31, offshore Angola is located in water depth of approximately 2000m; also the Great White, Silvertip and Tobago developments in the Gulf of Mexico are in water depths ranging from 2360 to 2940m, [1]), and with increasing tieback distances, calling traditional measurement employing three phase separator well testing into question. Moreover, new oil and gas developments commingled with existing infrastructures leads to various royalty payment requirements and further complicate the allocation process. These issues, coupled with widening operating envelope and improve measurement quality, is driving the development of multiphase meters to realize their full potential for reservoir monitoring, flow assurance calculations, production optimization, and reservoir engineering analysis [2], in addition to their traditional areas of application such as well surveillance or monitoring, well testing, production allocation metering and fiscal or custody transfer measurements.

Multiphase meters today are vital to oil companies' field development and production plans. This is because over the past decade multiphase measurement technology has undergone a significant transformation such that the number of multiphase flow meters (MPFMs) installed globally has continued to increase [3]. Industry analysts predict that there will be 1,000 additional subsea multiphase meters deployed by 2015 [4]. A number of factors are responsible for this rapid uptake of multiphase measurement technology. These are improved meter performances, decreases in meter costs, more compact meters enabling deployment of mobile systems, increases in oil prices, a wider assortment of operators [5] and the development of compact subsea meters.

Clamp-on gamma-densitometry is a suitable technique to facilitate non-intrusive multiphase flow metering as it does not require breaking into the pipeline for installation, thus eliminating the cost of production deferment [6]. Consequently, it is suitable for different line sizes, and can be retrofitted on land and offshore wells. The use of gamma-densitometry in multiphase flow analysis has been documented by a number of researchers. Gamma-densitometry, in conjunction with neural networks for multiphase flow measurement has been reported where the densitometer forms part of a sensor array. In addition, some researchers have used multiple gamma-densitometer units and neural networks to determine void fraction and flow regime [7]. In fact, several commercial MPFMs use gamma-densitometry techniques a part of their measurement systems [8]. This paper presents the exploitation of a single gamma-densitometer unit to determine both phase fractions and velocities to yield the individual phase flow rate of horizontal and vertically upward multiphase flows.

2 GAMMA DENSITOMETRY

A gamma densitometer comprises two principal components; namely a gamma ray source and a detector unit. Mounted diametrically opposite each other on a pipe section as schematically illustrated in Figure 1**,** it employs collimator structures to ensure the production of a narrow gamma beam [9]. Gamma densitometry is based on the fact that gamma rays are attenuated as they pass through matter due to interaction of their photons with the matter. The extent of this attenuation experience by the gamma rays depends on the energy of the gamma rays and the density of the absorbing matter.

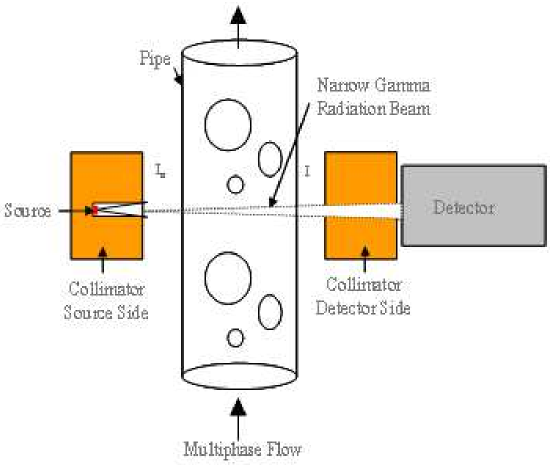

Fig. 1 - Gamma Densitometer (Arubi and Yeung, 2010)

Assuming the presence of a vacuum within the pipe, *(I_o)* will be the intensity of transmitted mono-energetic photons which strike the detector. This measurement corresponds to the number of photons transmitted from the source across the air outside of the pipe and through the pipe wall. If the pipe is filled with an absorbing matter, the intensity measured for a given photon energy follows the Beer-Lambert's exponential decay law:

$$I = I_o e^{-\gamma D} \tag{1}$$

The number of transmitted photons detected *(I)* after passing through a length *(D)* of absorbing material will depend on the linear attenuation coefficient *(γ)* of the absorbing material. The linear attenuation coefficient of a material will increase with material density with an approximately linear dependence for a single energy gamma beam, [10]. For three phase flow systems, the beam will attenuated by the oil, water and gas present in the flowline. Detailed treatment of gamma radiation and its detection is given by Prepost [11].

3 ARTIFICIAL NEURAL NETWORKS

Artificial Neural Network is an information processing concept that mimics the decision-making ability of the brain. Neural networks can also be viewed as massively parallel computing systems consisting of an extremely large number of simple processors with many interconnections (neurones) working in unison that can be configured for a specific application, such as pattern recognition or data classification, through a learning process.

Unlike conventional computing techniques that use a cognitive approach to problem solving, neural networks do not have to be programmed. Instead, a neural network system will learn to classify inputs through a training process (that might be supervised, unsupervised or reinforcement learning) in which the network is presented with a series of inputs and target outputs [7]. Based on this training data, the neural network will generate a mapping function between the inputs and outputs. Subsequent input data will then be processed using this relationship derived during the training process to produce corresponding output. Thus one can say that neural networks learn from experience. The main characteristics of neural networks are that they have the ability to learn complex nonlinear input-output relationships, use sequential training procedures, and adapt themselves to the data [12].

Numerous neural network models have been developed by researchers worldwide with each model having a different network structure, learning algorithm, performance capability and field of application, but all of these models stem from the original work of McCulloch and Pitts [13]. The most commonly used family of neural networks for pattern classification tasks are the feed-forward network (e.g. multi-layer perceptron). A detailed description of the different neural network models can be found in [14]. However, the feedforward multi-layer perceptron network implemented in this study will be examined here.

3.1 Feedforward Multi-layer Perceptron Model

Multi-layer perceptrons (MLP) are feed-forward neural networks with one or more layers of neurons between the input and output layers. They have been used as the basis of the majority of practical application of neural networks. As shown in Figure 2, the flow of information in the network begins with the input layer, proceeds through the hidden layers and ends at the output layer.

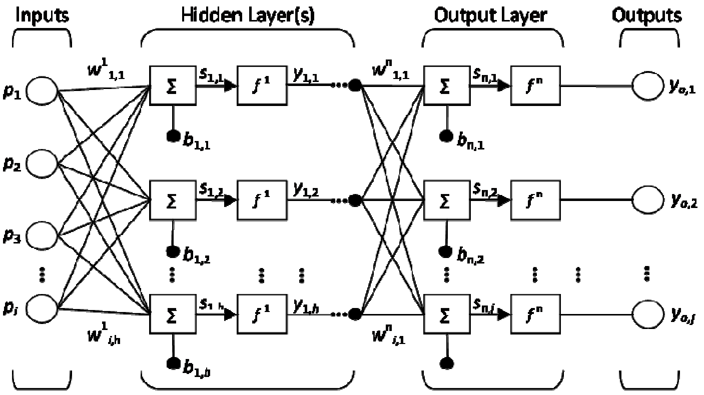

Fig. 2 - Architecture of a Multi-layer Perceptron
(Blaney and Yeung, 2007)

Each input *(p)* is connected to all nodes in the first hidden layer. If there are more than one hidden layers, all outputs from the preceding layer are input to each node in the successive layer. For all nodes, the inputs are first multiplied by their respective weights *(w)*, and then summed *(s)* up with subsequent addition of a bias *(b)*. The resulting value is used as the input to an activation function *(f)*. The first hidden layer output $(y_{1,h})$ from each processing nodes in the first hidden layer, with I inputs parameters, can be expressed by:

$$y_{1,h} = f^{1}\left[\sum_{i=1}^{I}\left(w_{i,h}^{1}\,p_i + b_{1,h}\right)\right] \tag{2}$$

Treating the system as a two-layer system (n = 2), the outputs ($y_{o,j}$) can be expressed by:

$$y_{o,j} = f^{2}\left[\sum_{h=1}^{H}\left[w_{h,j}^{2}\left[f^{1}\left[\sum_{i=1}^{I}\left(w_{i,h}^{1}\,p_i + b_{1,k}\right)\right]\right] + b_{2,j}\right]\right] \tag{3}$$

Defining the network architecture is a key stage in neural network analysis. For applications where the number of input and output neurons is fixed, the difficulty in defining the network architecture is reduced to the selection of the type(s) of activation function, the number of hidden layers and the number of neurons to be employed in the model. According to [15], a two-layer perceptron with sigmoid non-linearity can approximate any function with arbitrary accuracy. There are no rules for the selection of the number of hidden nodes but, the rule of thumb is that, the more complex the function one is attempting to model, the greater the number of hidden nodes required. Deciding on the number of hidden nodes is quite tricky because if too many nodes are used the network will memorise the training data thereby displaying poor generalisation, on the other hand, too few hidden nodes will result in a system with insufficient parameters to model the underlying function and severe underfitting will be experienced [16].

Multi-layer networks use a variety of learning techniques, popular amongst them is the back-propagation algorithm. Here, the output values are compared with the correct answer to compute the value of some predefined error-function. By various techniques, the error is then fed back through the network. Using this information, the algorithm adjusts the weights of each connection in order to reduce the value of the error function by some small amount. After repeating this process for a sufficiently large number of training cycles, the network will usually converge to some state where the error of the calculations is small. In this case, one would say that the network has *learned* a certain target function [17].

4 EXPERIMENTAL WORK

The multiphase test facility at Cranfield University is used for flow assurance, multiphase metering and control systems research. It is a fully automated high pressure test facility designed to supply a controlled and measured amount of oil, water and air mixture from the flow metering area into the test area and finally into the phase separation area where the oil, water and air are separated. After separation in a horizontal three-phase gravity separator, the oil and water are cleaned in their respective coalescers before returning to their storage tanks while the air is exhausted into the atmosphere [18]. Figure 3 shows the schematic of the multiphase test facility. The test area consists of a 101.6mm and 50.8mm diameter flow loops. The 101.6mm loop is a 55m long, 2° downward inclined pipeline joined to a catenary shaped riser with a vertical height of 10.5m. The 50.8mm loop is a 40m long horizontal pipeline, connected to a 10.5m height vertical riser.

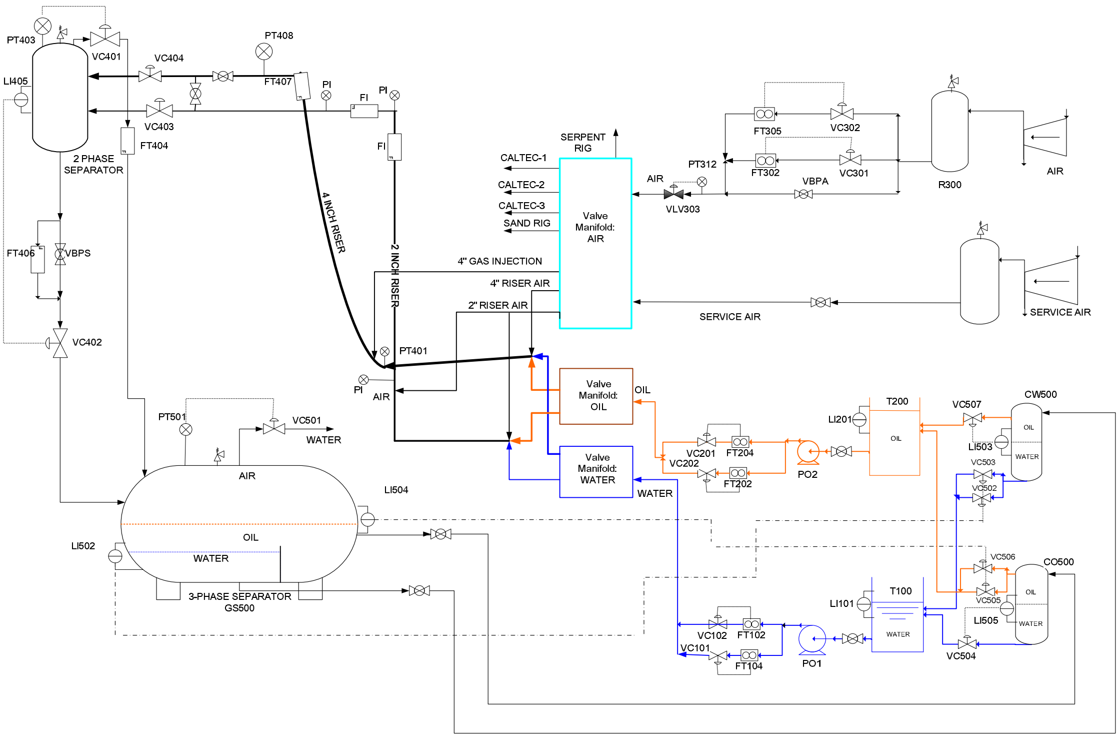

Fig. 3 - Cranfield University Multiphase Loop showing 101.6mm Catenary Riser and 50.8mm Vertical Riser (Cao and Yeung, 2009)

4.1 Experimental Apparatus

The multiphase test facility at Cranfield University is designed to process continuous flow of air, oil and water. The facility has a maximum operating pressure of 25 barg and the test fluids comprise air, tap water (doped with biocide) and BP-7269 lubricating oil (ρ = 815 kg/m3 and μ = 0.004 Pa.s at 20ºC). The flow loop can deliver up to 140 m3/h of oil and water; and 4250 m3/h of free air at 7 barg and is equipped with a state-of-the-art DeltaV process control and management system.

Two gamma densitometer units supplied by Neftemer Ltd consist of lead-filled source housing, a detector unit, and a data processing box. These units were vertically installed at the top of the 101.6mm and 50.8mm loop and horizontally at the riser base of the 50.8mm loop. The gamma densitometer contains a 6.6×10^9Bq caesium-137 source. The detector unit which contains NaI crystals, provides two separate gamma counts readings corresponding to the high-energy direct photons (hard signal) and the low-energy scattered radiation (soft signal) from the Cs-137 radioisotope. Average counts measurements for both energy levels is pass to a local PC via a data processing unit for storage and offline analysis. These raw data files can be exported into any signal analysis software (e.g. MATLAB) for further processing.

4.2 Experimental Procedure

A comprehensive experimental campaign comprising of air-liquid two and air-liquid-liquid three phase flows was undertaken. The two phase tests consisted of 260 experimental data points with water superficial velocities from 0.12 to 0.85 m/s and gas superficial velocities from 0.15 to 3.09 m/s while a total of 372 test runs were conducted for the three phase flows covering a range that is typical of operating conditions in the oil and gas industry. Figure 4 shows the vertical flow regime map generated from probability mass function plots of the gamma densitometer data.

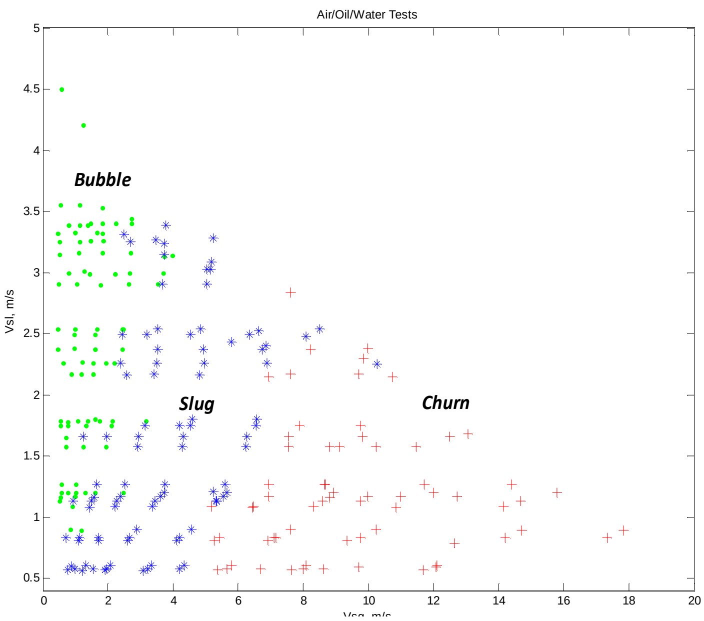

Fig. 4 - 50.8mm Flow Loop Vertical Regime Map for Three Phase Tests

For each test point, the flow conditions are set and monitored using the Delta V plant automation system. Gamma counts recording, initiated when steady-state conditions were attained, was undertaken for a period of 30 minutes for each measurement point on the test matrix. Statistical features were extracted from the time varying gamma hard and soft counts signals and used as input parameters for the neural network model. Features were also extracted from a third synthesized 'combined' signal that is a fusion of the hard and soft counts. From literature survey, it was found that an effective feature vector permutation will be obtained through the combination of features from each of the information domains. Table 1 lists the features selected for examination.

Neural network output sensitivity-based feature saliency measure was used as the feature selection technique to select representative features in this study. Reference output target values; namely the gas and liquid superficial velocities (V_{sg} and V_{sl} respectively) and the liquid phase water cut (WC), were obtained from the test facility's DeltaV system. The zero-mean and unit variance normalisation (ZMUV) was the pre-processing routines used. ZMUV normalises the data set to ensure that each vector is scaled so that its mean is zero and its variance is 1, thus, reducing the dimensionality of the input vector.

Table 1 - Statistical Features Selected For Examination

	Information Domain				
Feature	**Symbol**	**Amplitude**	**LPC**	**LSF**	**ACF**
Mean Value	AV	✓			
Standard Deviation	SD	✓			
Coefficient of Skewness	CS	✓			
Coefficient of Kurtosis	CK	✓			
Signal Total Energy	E_T	✓			
Linear Prediction Coefficient 1	LPC1		✓		
Linear Prediction Coefficient 2	LPC2		✓		
Linear Prediction Coefficient 3	LPC3		✓		
Linear Prediction Coefficient 4	LPC4		✓		
Linear Prediction Coefficient 5	LPC5		✓		
Linear Prediction Error	E_R		✓		
Line Spectral Frequency 1	LSF1			✓	
Line Spectral Frequency 2	LSF2			✓	
Line Spectral Frequency 3	LSF3			✓	
Line Spectral Frequency 4	LSF4			✓	
Line Spectral Frequency 5	LSF5			✓	
ACF Coefficient at Minimum	ACF1				✓

ACF Lag Minimum	ACF2				✓
ACF Coefficient at Maximum	ACF3				✓
ACF Lag Maximum	ACF4				✓

4.3 MLP Model

A feedforward multilayer perceptron (MLP) model was developed with the superficial gas velocity (V_{sg}), superficial liquid velocity (V_{sl}) and water cut (WC) as the output nodes as illustrated in Figure 5. The 260 experimental data of the air-water two phase flow (in the 50.8mm rig) and the 744 data points of the air-oil-water three phase flow (in the 101.6mm rig) were divided into training and test sets with two-third used for training the network and one-third for testing purposes.

Prior to running the neural network simulation, the network architecture was determined by specifying the number of hidden layers and the number of neurons in each layer. Recent work has revealed that optimal performance can only be achieved if architecture is chosen according to the peculiarity of the problem. After several trials, the final architecture was defined as [n – 12 – 2] for the air-water two phase flow data and [n – 14 – 3] for the air-oil-water three phase flow data. Where n – is the number of input feature vectors (variable); 12 and 14 – are the number of neurons in the hidden layer (fixed); 2 and 3 – are the number of output neurons, i.e., one each for the target (fixed).

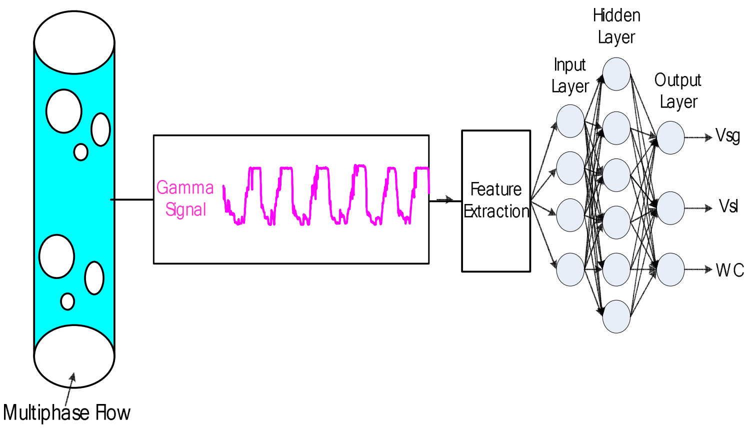

Fig. 5 - The MLP Neural Network Model Concept

Batch training approach, whereby the training all the data is fed into the network and the weights of the network updated only when the entire batch of the data has been processed, was utilised in this study. Bayesian regularisation with the use of Levenberg-Marquardt (LM) algorithm was employed in training the network and adjusting its weights repeatedly until the network architecture had optimised generalised properties. After training, the neural network model was assessed to evaluate its repeatability capabilities.

In order to get a quantitative comparison of the neural network performance, an error criterion, calculated as a relative error over the measurable flow range of each phase was established as given by Equation 4. The target accuracy for this work was set at ±5% for the air-water two phase flow data and ±10% for the air-oil-water three phase flow data for each of their target output.

$$E_r = \frac{Y_m - Y_a}{Y_{\max} - Y_{\min}} \times 100 \qquad (4)$$

Where (Y_m) is measured variable, (Y_a) is the actual or reference measurement and $(Y_{max} - Y_{min})$ is the measurable range. This performance classification method has been widely used by several researchers [18].

5 RESULTS

Flow rate measurement results from the air-water two phase flow (101.6mm flow loop) obtained for both the gas and liquid superficial velocities with the gamma densitometer hard, soft and hard-soft combined signals are presented in Table 2. At a measurement error band of

±10%, 100% of the data points were predicted correctly for both the gas and liquid superficial velocities for all the input features.

For the hard signal, and at an error band of ±5%, 91% of the test data points were correctly predicted for the gas superficial velocities and 80% for the liquid superficial velocities. Prediction results for the soft gamma signal outperforms those of the hard signals at the ±5% error band as 95% of the test data points were correctly predicted for both the gas and liquid superficial velocities, see Figure 6.

Combining features from both soft and hard gamma signal yielded results similar to those obtained with the soft gamma signals only. That is 95% of the test data points were predicted to within ±5% target value for the gas and liquid superficial velocities.

Table 2 - FMLP Model Predictions for the 101.6mm Data

Input Features	($E_r \leq \pm 10\%$)		($E_r \leq \pm 5\%$)	
	V_{sg}	V_{sl}	V_{sg}	V_{sl}
Hard Gamma	100%	100%	91%	80%
Soft Gamma	100%	100%	95%	95%
Hard-Soft Combined	100%	100%	95%	95%

Flow rate and water cut measurement results from the air-oil-water three phase flow (50.8mm flow loop) obtained with the gamma densitometer hard, soft and hard-soft combined signals in are presented in Table 3. It contains a summary of the flow rates and water cut prediction performance. In general, the results from the gamma densitometer mounted in the horizontal orientation are much better than those gotten from one the mounted vertically. Also it was observed that combining the hard and soft signals did not necessarily improve the prediction performance of the network.

Table 3 - FMLP Model Predictions for the 50.8mm Data

Input Features	Horizontal Gamma Data E_r (±10%)			Vertical Gamma Data E_r (±10%)		
	V_{sg}	V_{sl}	WC	V_{sg}	V_{sl}	WC
Hard Gamma	95%	80%	42%	90%	67%	43%
Soft Gamma	95%	73%	41%	91%	70%	42%
Hard-Soft Combined	95%	76%	42%	92%	68%	40%

The MLP neural network model exhibited good gas classification suggesting that the extracted features yielded good correlation with the multiphase flow gas and liquid phase properties across the measurement range studied and discrepancies in the correlations between flow regimes could be sufficiently modelled by a single neural network model. However, with the current feature set, it is not possible to obtain satisfactory liquid phase water cut parameter predictions using only a single MLP neural network for the three phase flow data.

There is strong tendency for vertical multiphase flow to contain asymmetries and higher phase slip. These asymmetries alter the flow pattern as 'seen' by the gamma densitometer and thus the statistical features extracted there from. The implication of this is that the performance of a pattern recognition model based on the features extracted from a horizontally mounted densitometer will differ from that mounted vertically. This study has shown that the horizontally mounted gamma densitometer produces better prediction results than those from the vertical.

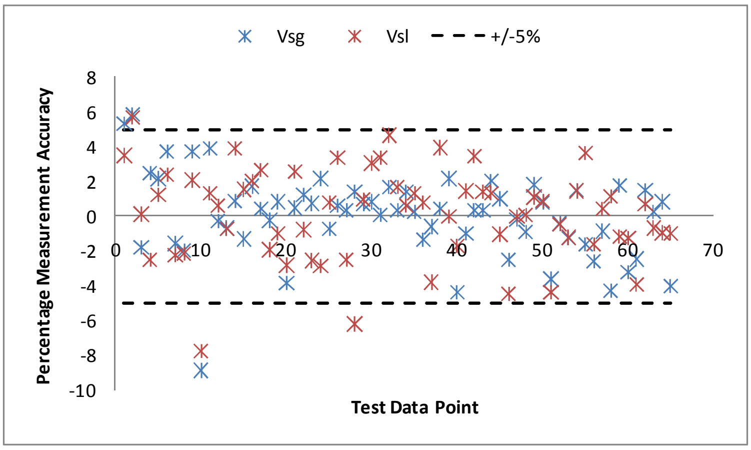

Fig. 6 - Prediction Performance from the Soft Energy Gamma Features (50.8mm Flow Loop Data)

Previous studies in pattern recognition techniques for horizontal multiphase flows were based on the assumption/assertion that horizontal flows has more features than vertical flows (e.g. in terms of flow regime, there are stratified, wavy stratified, bubbly, plug, slug, annular and mist flow for horizontal flows compared with bubbly, slug, churn, annular and mist for vertical flows), thus there is a better chance of using feature extractions to determine flow rates employing neural network approach, thereby achieving better prediction results than vertical flows. This is the first time this assumption/assertion is been demonstrated.

6 CONCLUSION

The exploitation of a single gamma-densitometer with pattern recognition approaches to measure individual phase flow rates in multiphase flow was investigated. The aim is to establish the suitability of gamma-based techniques as a compact and cost effective solutions of on-line continuous multiphase flow measurement for well testing, production monitoring, production optimisation, process control and automation purposes. Specific conclusion drawn from this study are:

1. Signal analysis of the densitometer data in the time and frequency domain gave a good indication of the gas and liquid phase distribution in the flow and discriminatory correlations between statistical features of the gamma counts data and key multiphase flow parameters were revealed. It was shown that, for the two phase flow data, individual phase flow measurements to within ±5% are possible with an appropriate network set up.
2. It was further established that, with the current feature set from the three phase flow data, satisfactory liquid phase water cut parameter predictions using only a single MLP network, was not possible.
3. Furthermore, the result from this study shows that the horizontally mounted gamma densitometer produces better prediction results than those from the vertical.
4. We opined that, given the results presented here and with further research and development work, the use of gamma-densitometry, in conjugation with a pattern recognition model, could offer an economical, non-intrusive and robust measurement solution to meet the requirements of the Petroleum Industry.

7 ACKNOWLEDGEMENTS

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